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Grossberg et al.

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(54) **METHOD AND SYSTEM FOR ENHANCING DATA QUALITY**

(75) Inventors: **Michael D. Grossberg**, New York, NY (US); **Shree K. Nayar**, New York, NY (US)

(73) Assignee: **The Trustees of Columbia University in the City of New York**, New York, NY (US)

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PCT Pub. Date: **Oct. 9, 2003**

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(51) **Int. Cl.**
H04N 7/12 (2006.01)

(52) **U.S. Cl.** **375/240.27**; 375/240; 375/240.26

(58) **Field of Classification Search** 375/240, 375/240.01, 240.12, 240.26, 240.27
See application file for complete search history.

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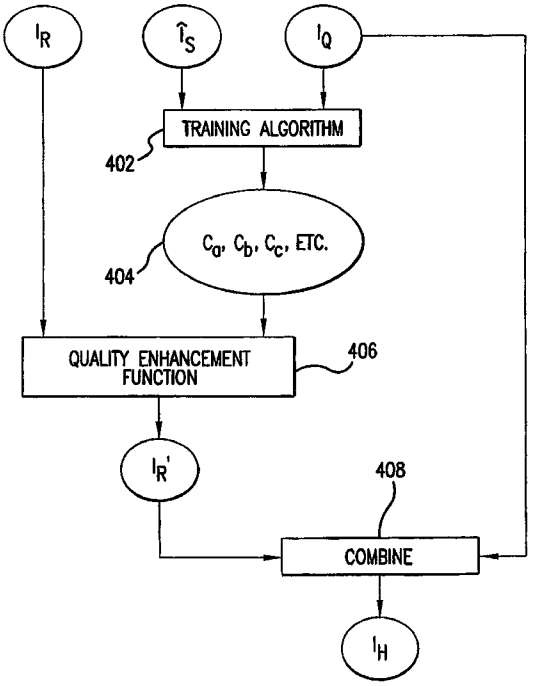
Primary Examiner—Allen Wong
(74) *Attorney, Agent, or Firm*—Baker Botts LLP

(57) **ABSTRACT**

The quality (e.g., resolution) of image data, video data, and sound data representing a scene or signal is enhanced by a quality enhancement function trained on high quality and low quality representations of a portion of the same scene or signal. The enhancement function is thus optimized to the most relevant input. A training algorithm uses low quality image of a scene or scene portion, along with a high quality image of the same scene or scene portion, to optimize the parameters of a quality enhancement function. The optimized enhancement function is then used to enhance other low quality images of the scene or scene portion. Sound data is enhanced by using a low resolution sample of a portion of a signal, and a high resolution sample of the same signal portion, to train a quality enhancement function which is then used to enhance the remainder of the signal.

38 Claims, 16 Drawing Sheets



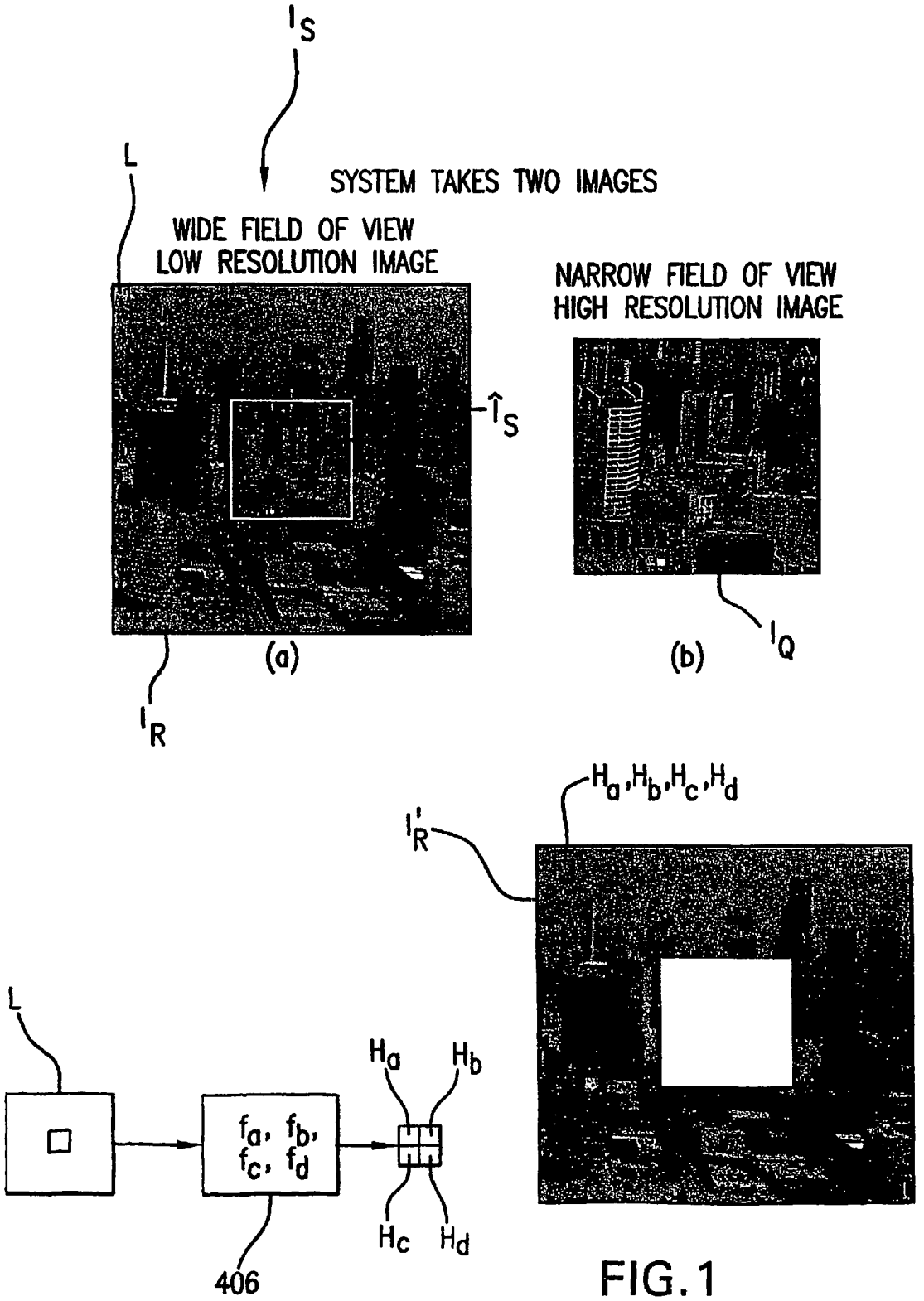

I_S
L
SYSTEM TAKES TWO IMAGES
WIDE FIELD OF VIEW
LOW RESOLUTION IMAGE
NARROW FIELD OF VIEW
HIGH RESOLUTION IMAGE
$\hat{I}_S$
(a)
(b)
I_Q
I_R
H_a, H_b, H_c, H_d
I'_R
L
H_a
H_b
$f_a, f_b,$
f_c, f_d
H_c
H_d
406

FIG. 1

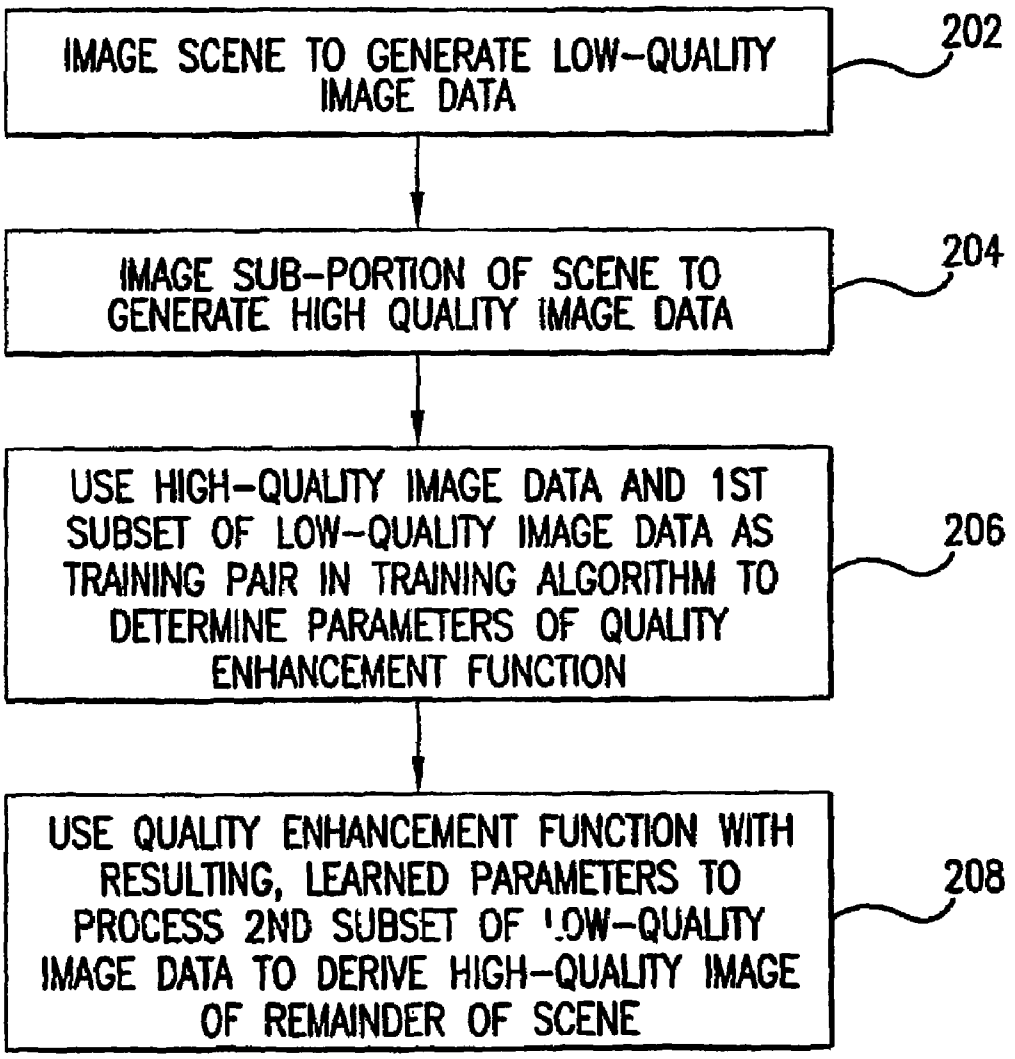


IMAGE SCENE TO GENERATE LOW-QUALITY IMAGE DATA
202
IMAGE SUB-PORTION OF SCENE TO GENERATE HIGH QUALITY IMAGE DATA
204
USE HIGH-QUALITY IMAGE DATA AND 1ST SUBSET OF LOW-QUALITY IMAGE DATA AS TRAINING PAIR IN TRAINING ALGORITHM TO DETERMINE PARAMETERS OF QUALITY ENHANCEMENT FUNCTION
206
USE QUALITY ENHANCEMENT FUNCTION WITH RESULTING, LEARNED PARAMETERS TO PROCESS 2ND SUBSET OF LOW-QUALITY IMAGE DATA TO DERIVE HIGH-QUALITY IMAGE OF REMAINDER OF SCENE
208

FIG. 2

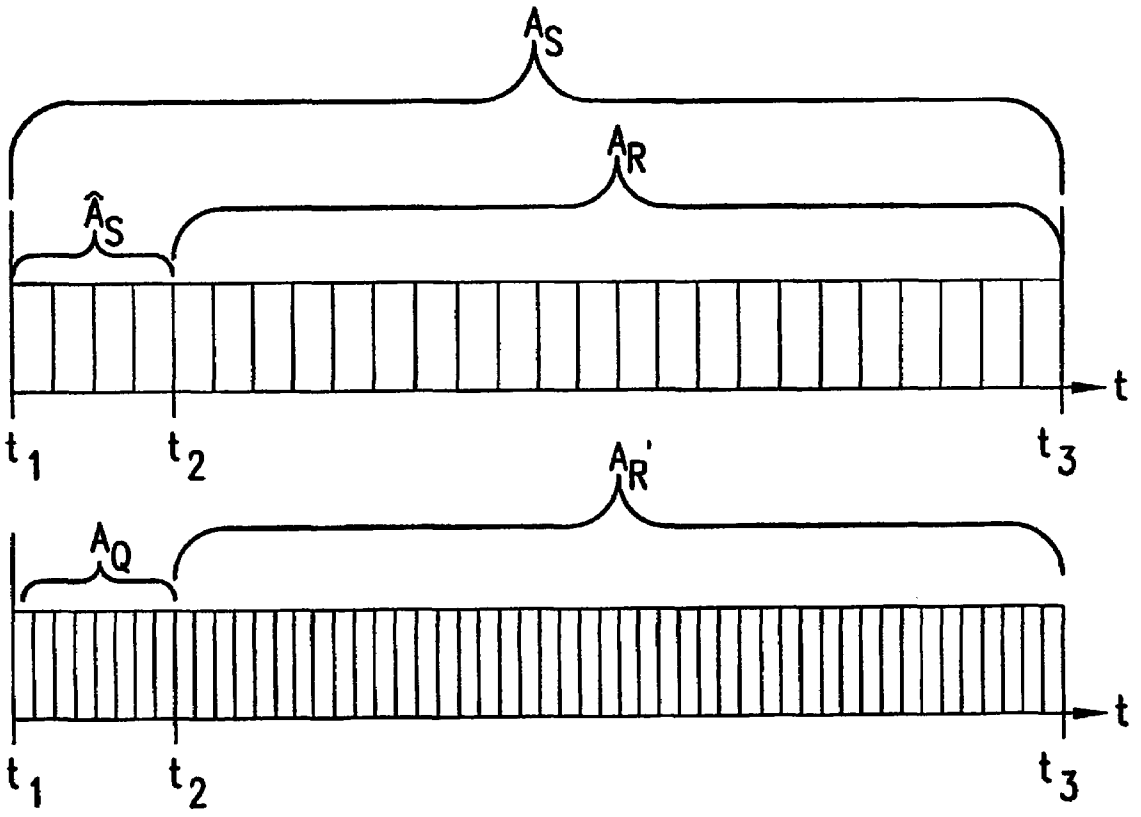


FIG.3

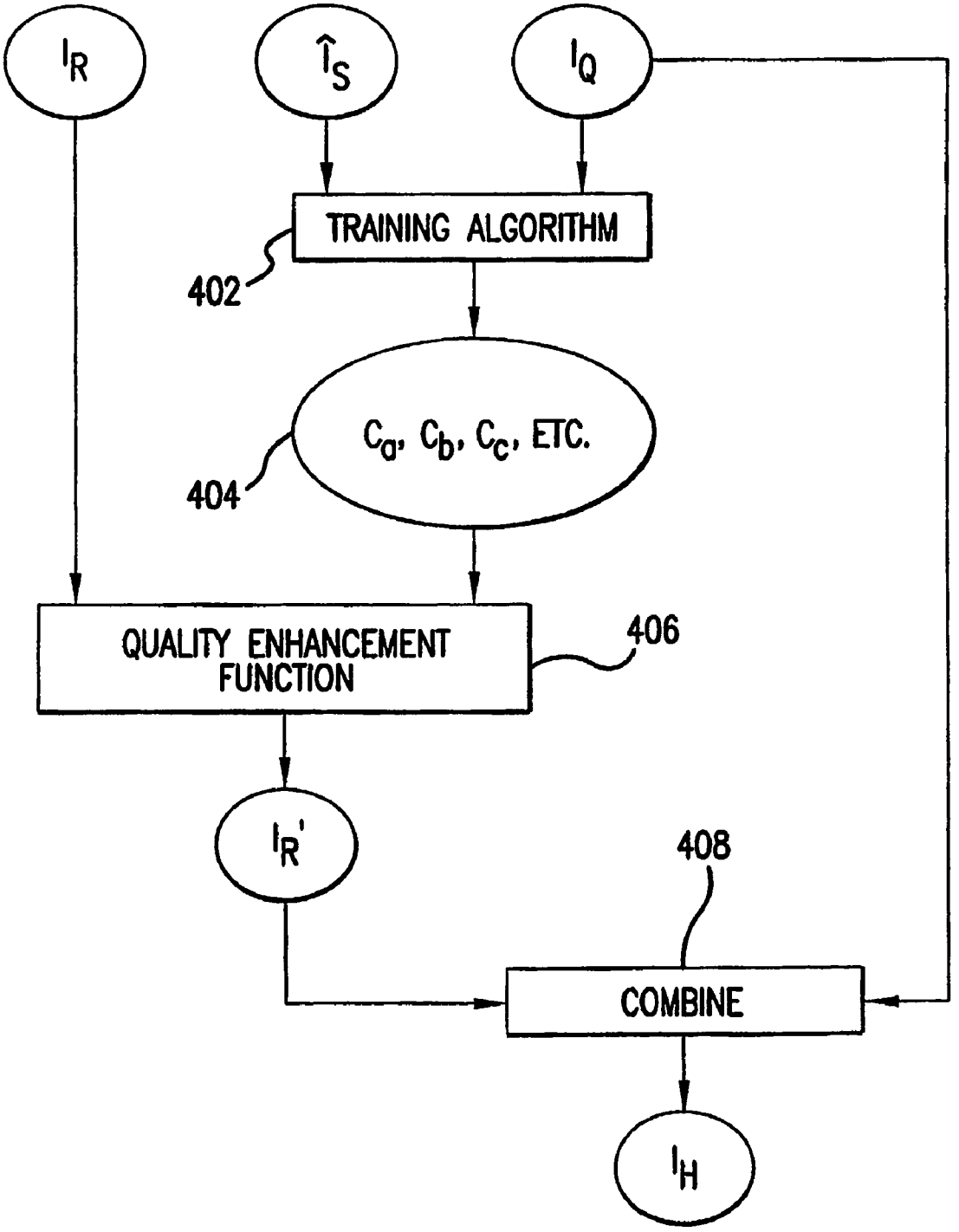

I_R
$\hat{I}_S$
I_Q
TRAINING ALGORITHM
402
C_a, C_b, C_c, ETC.
404
QUALITY ENHANCEMENT FUNCTION
406
I_R'
408
COMBINE
I_H

FIG.4

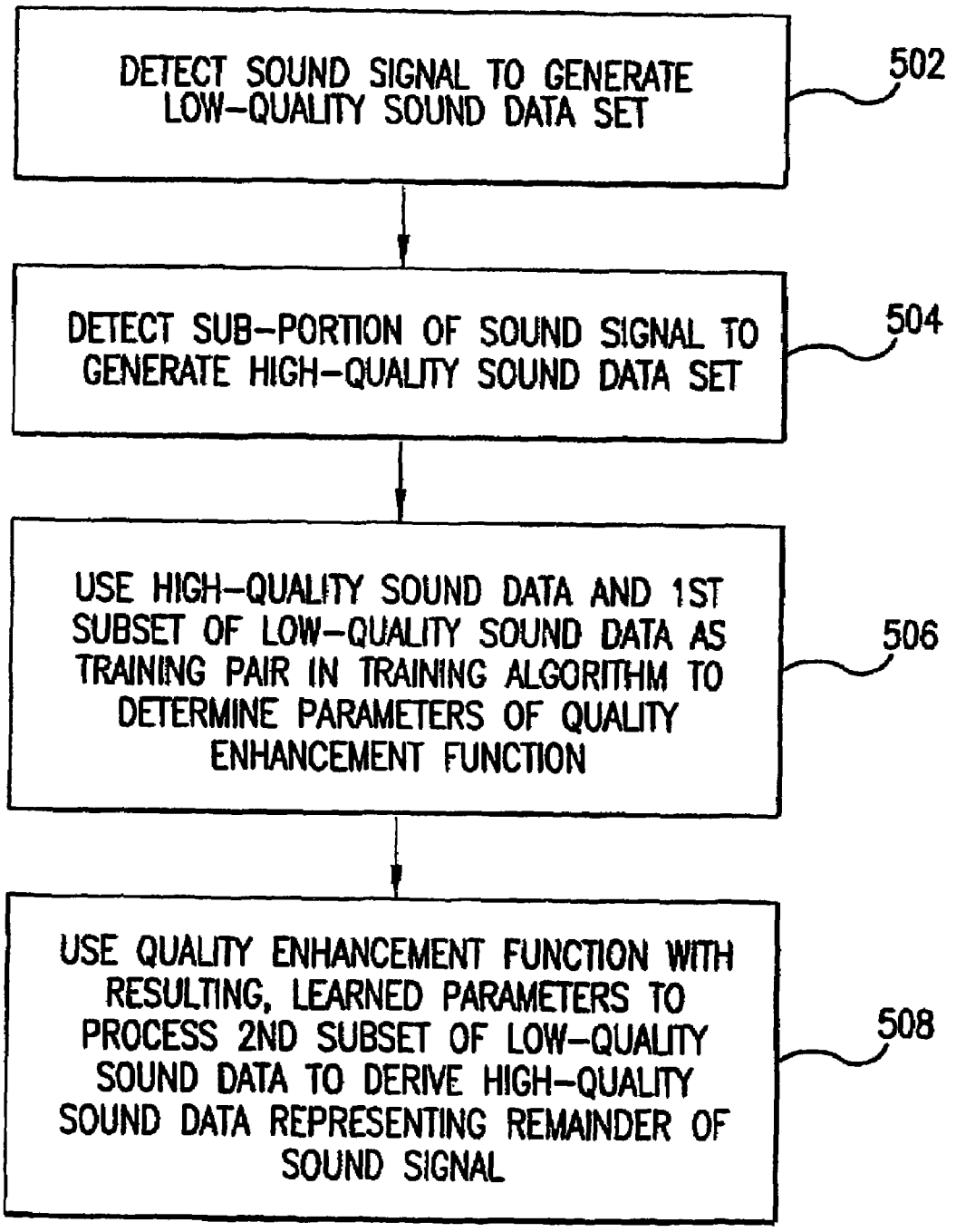

DETECT SOUND SIGNAL TO GENERATE LOW-QUALITY SOUND DATA SET
502
DETECT SUB-PORTION OF SOUND SIGNAL TO GENERATE HIGH-QUALITY SOUND DATA SET
504
USE HIGH-QUALITY SOUND DATA AND 1ST SUBSET OF LOW-QUALITY SOUND DATA AS TRAINING PAIR IN TRAINING ALGORITHM TO DETERMINE PARAMETERS OF QUALITY ENHANCEMENT FUNCTION
506
USE QUALITY ENHANCEMENT FUNCTION WITH RESULTING, LEARNED PARAMETERS TO PROCESS 2ND SUBSET OF LOW-QUALITY SOUND DATA TO DERIVE HIGH-QUALITY SOUND DATA REPRESENTING REMAINDER OF SOUND SIGNAL
508

FIG.5

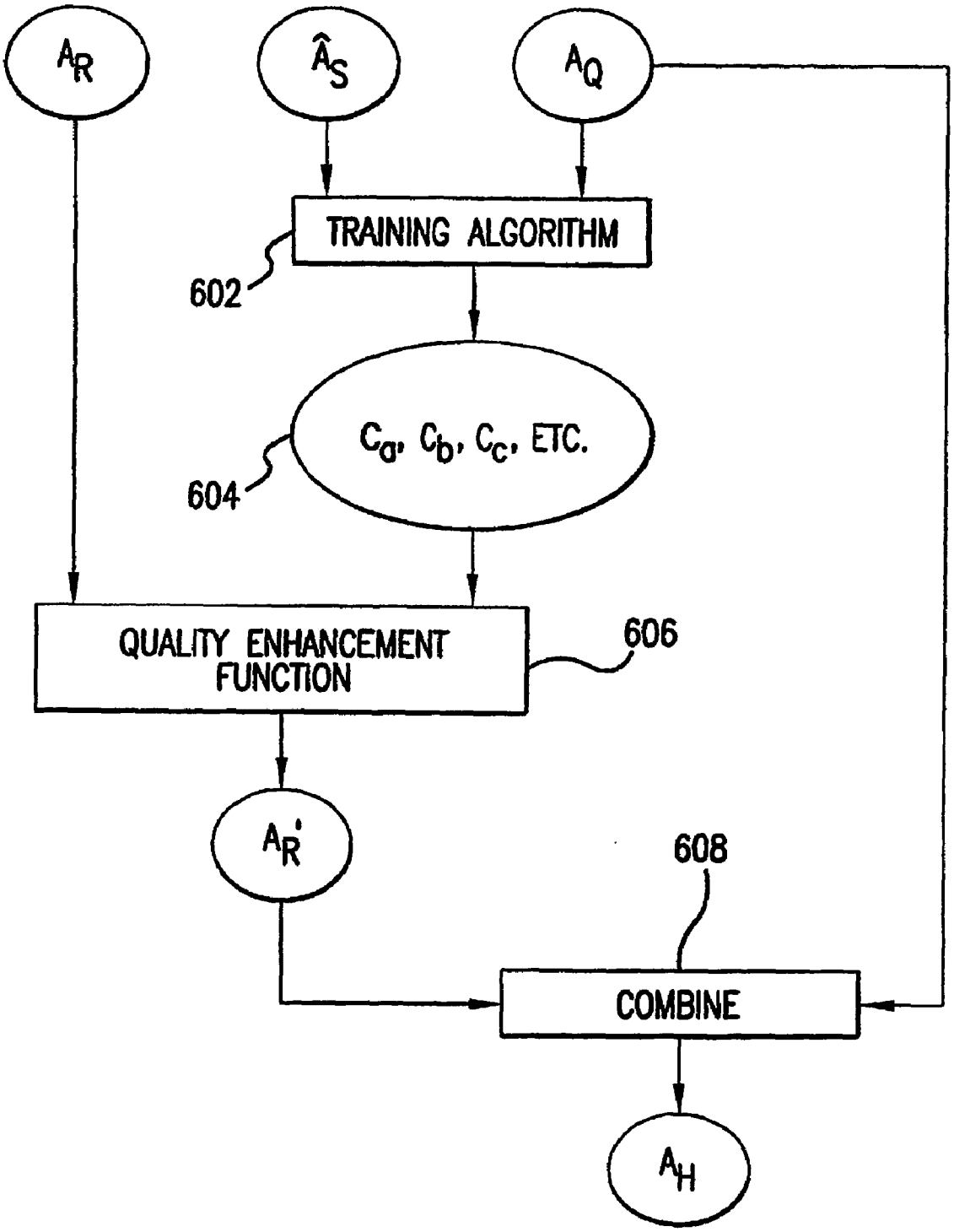

A_R
$\hat{A}_S$
A_Q
TRAINING ALGORITHM
602
C_a, C_b, C_c, ETC.
604
QUALITY ENHANCEMENT FUNCTION
606
A_R'
608
COMBINE
A_H

FIG. 6

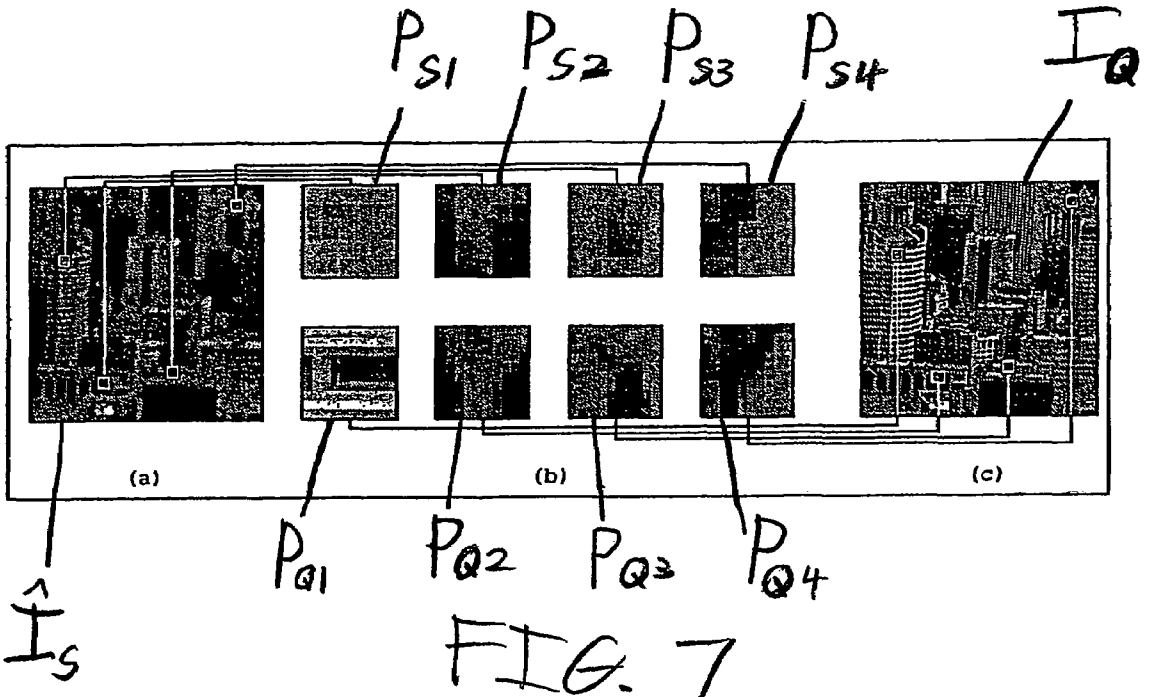


FIG. 7

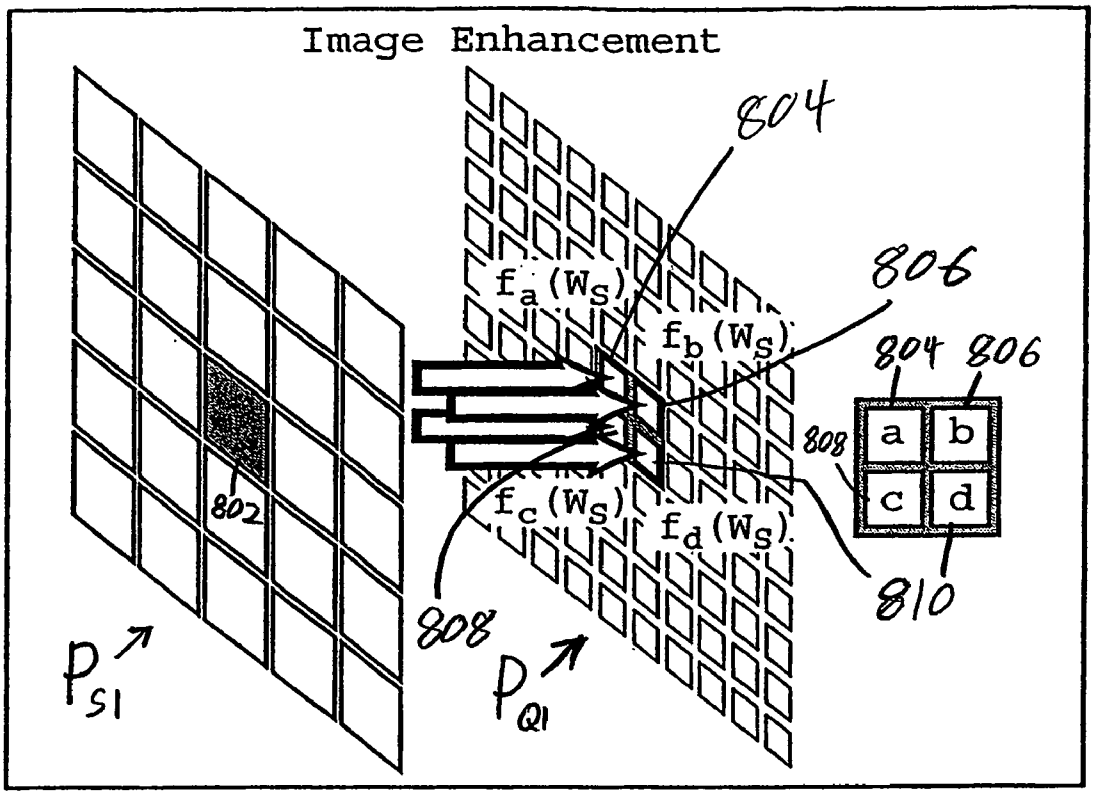


Image Enhancement
804
806
$f_a(W_S)$
$f_b(W_S)$
$f_c(W_S)$
$f_d(W_S)$
804 806
808
a
b
c
d
802
808
810
P_{S1}
P_{Q1}

FIG. 8

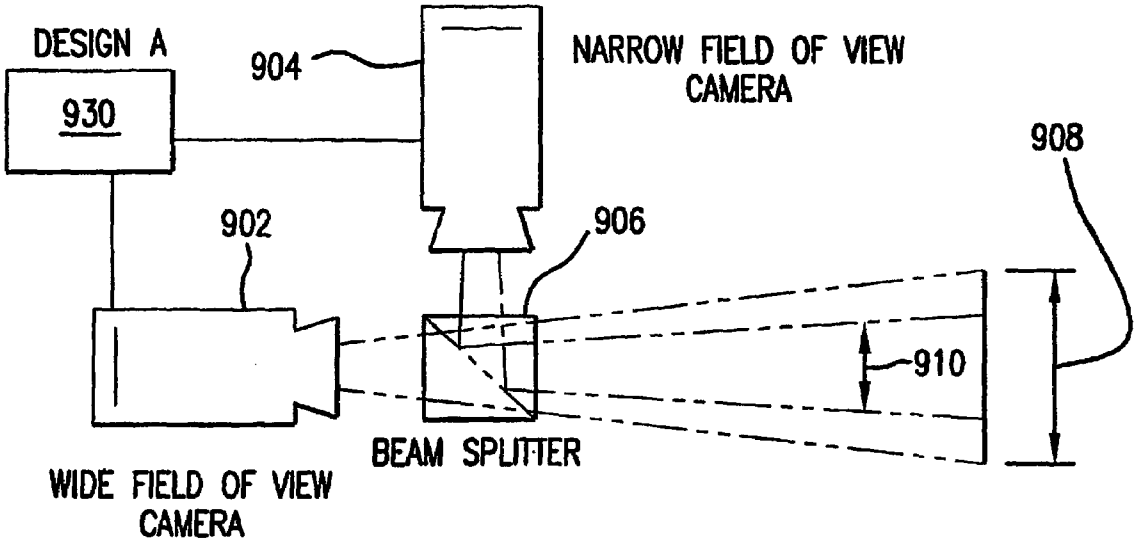

DESIGN A
930
904
NARROW FIELD OF VIEW CAMERA
908
902
906
910
BEAM SPLITTER
WIDE FIELD OF VIEW CAMERA

FIG.9A

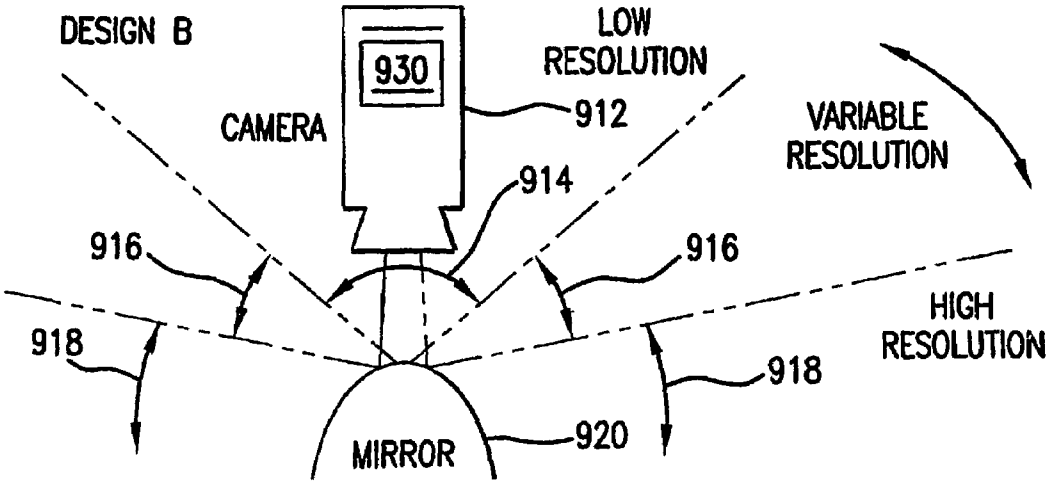

DESIGN B
930
LOW RESOLUTION
912
CAMERA
914
VARIABLE RESOLUTION
916
916
HIGH RESOLUTION
918
918
MIRROR
920

FIG.9B

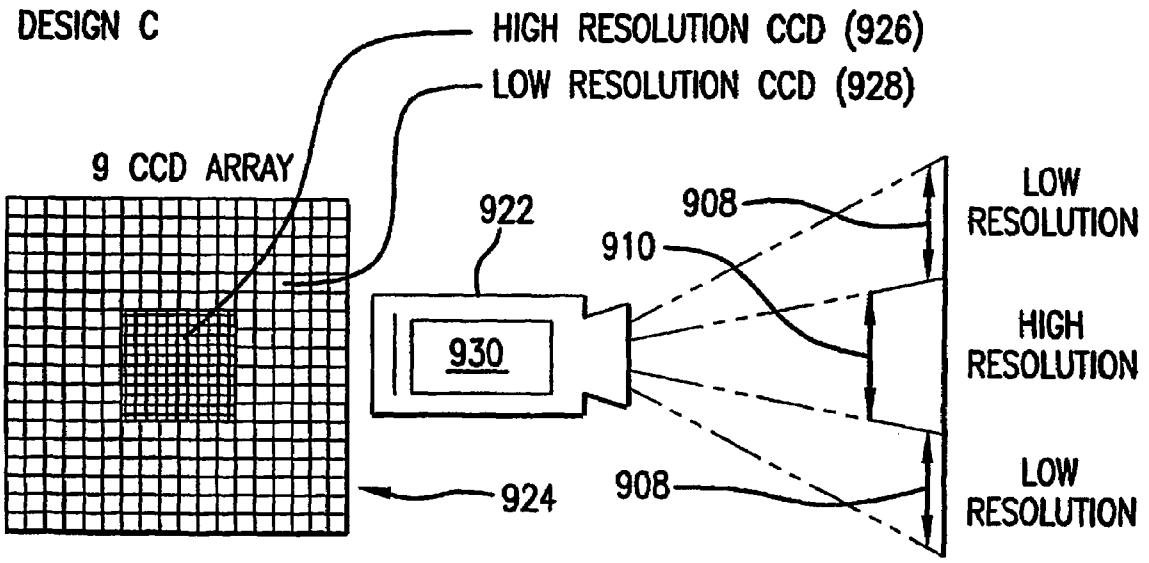

DESIGN C
HIGH RESOLUTION CCD (926)
LOW RESOLUTION CCD (928)
9 CCD ARRAY
922
908
910
930
LOW RESOLUTION
HIGH RESOLUTION
LOW RESOLUTION
924
908

FIG.9C

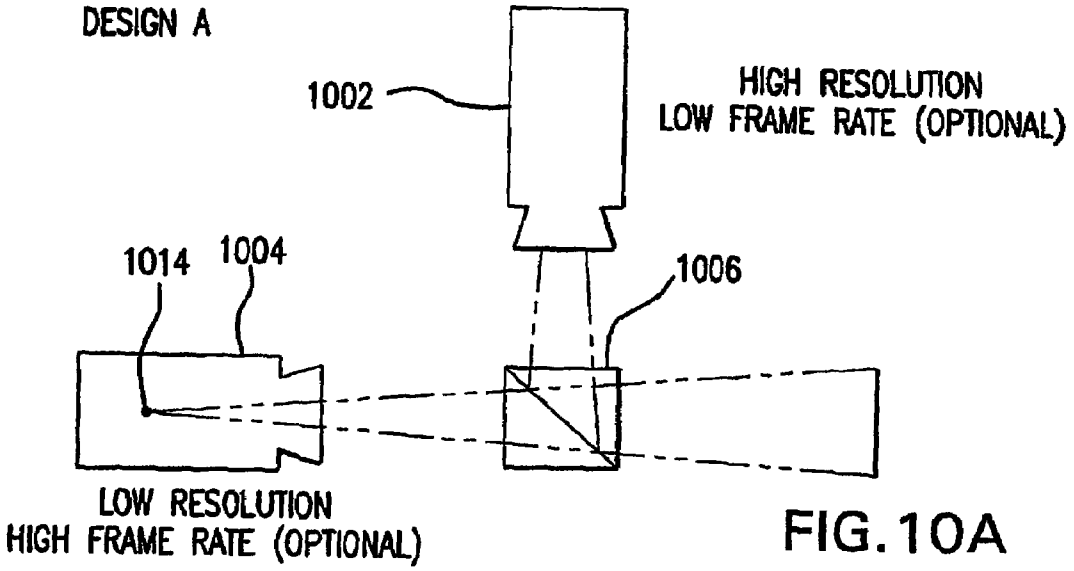


FIG.10A

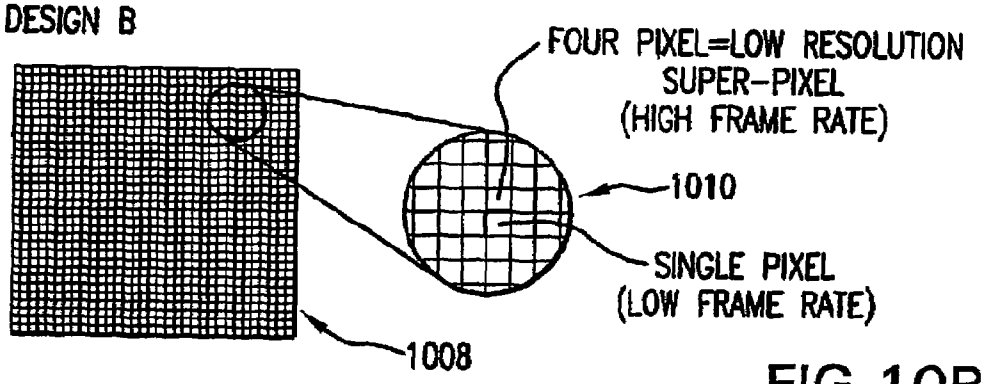
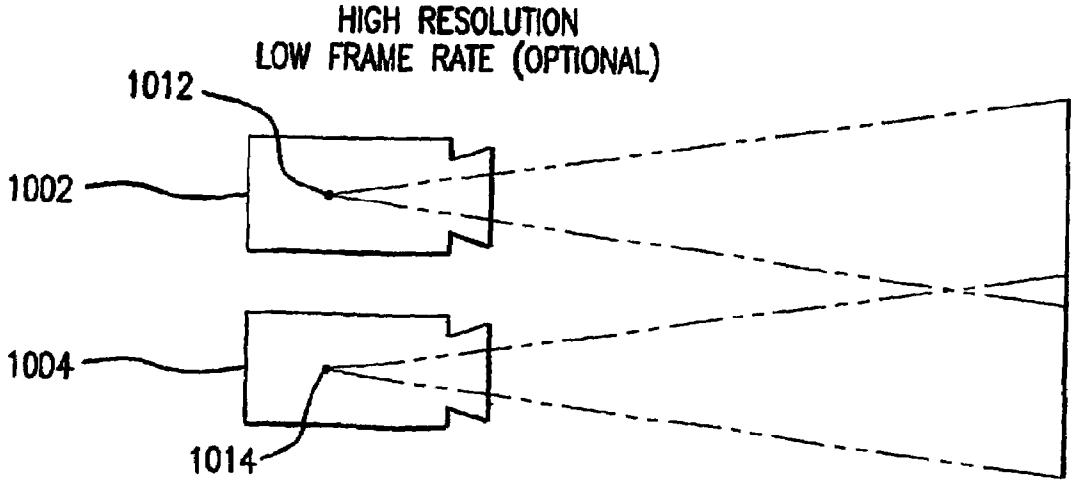


FIG.10B



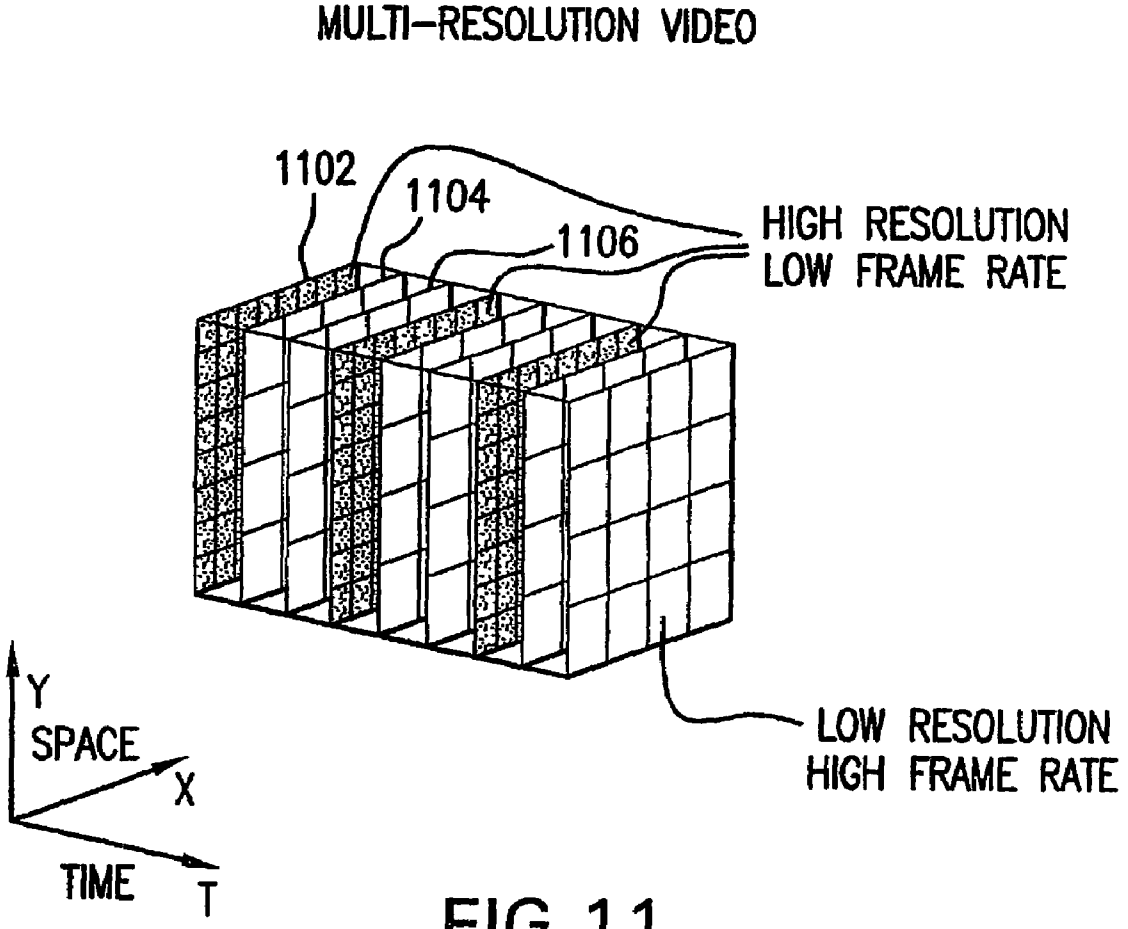

MULTI-RESOLUTION VIDEO
1102
1104
1106
HIGH RESOLUTION
LOW FRAME RATE
LOW RESOLUTION
HIGH FRAME RATE
Y
SPACE
X
TIME
T

FIG. 11

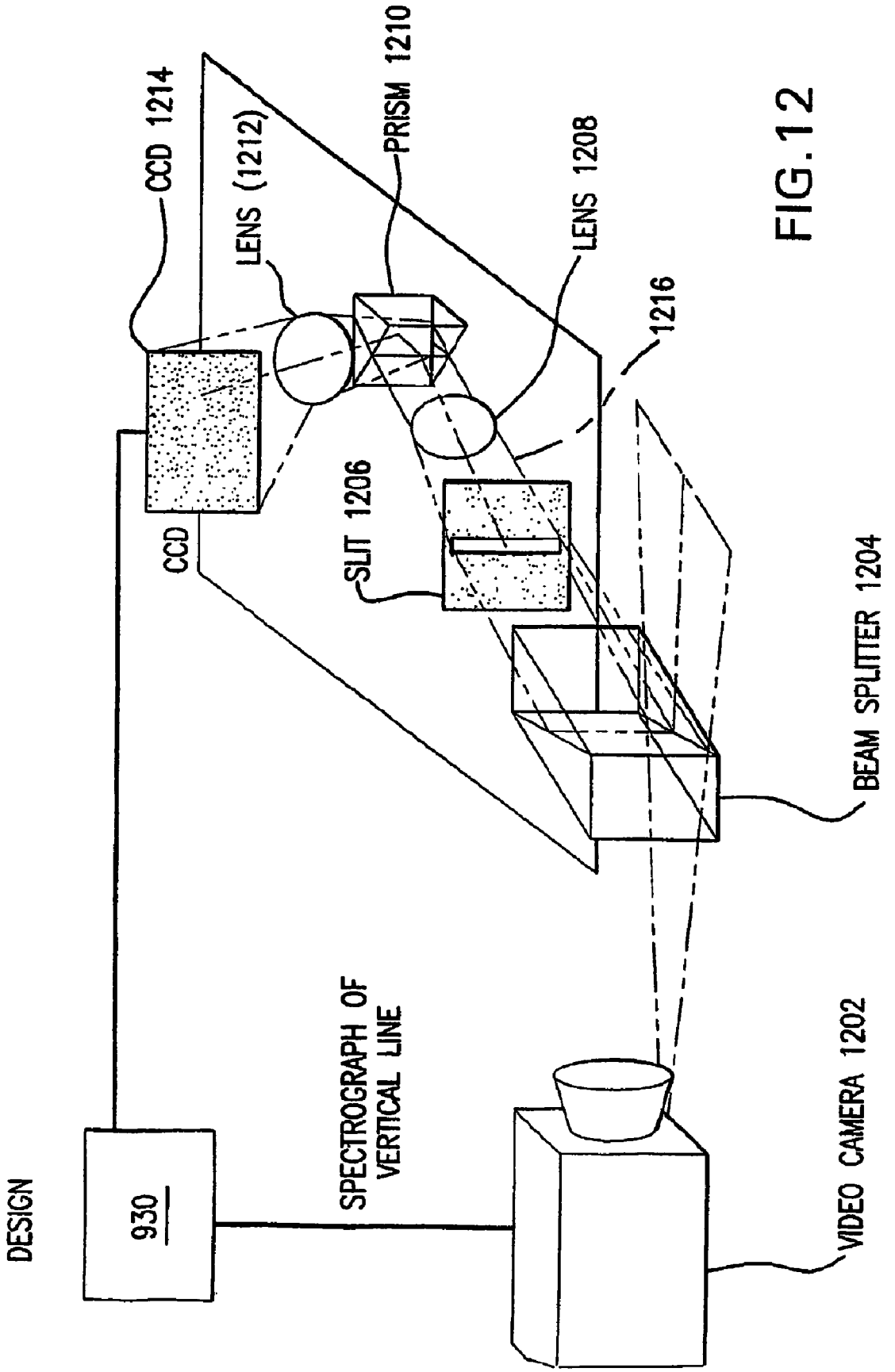
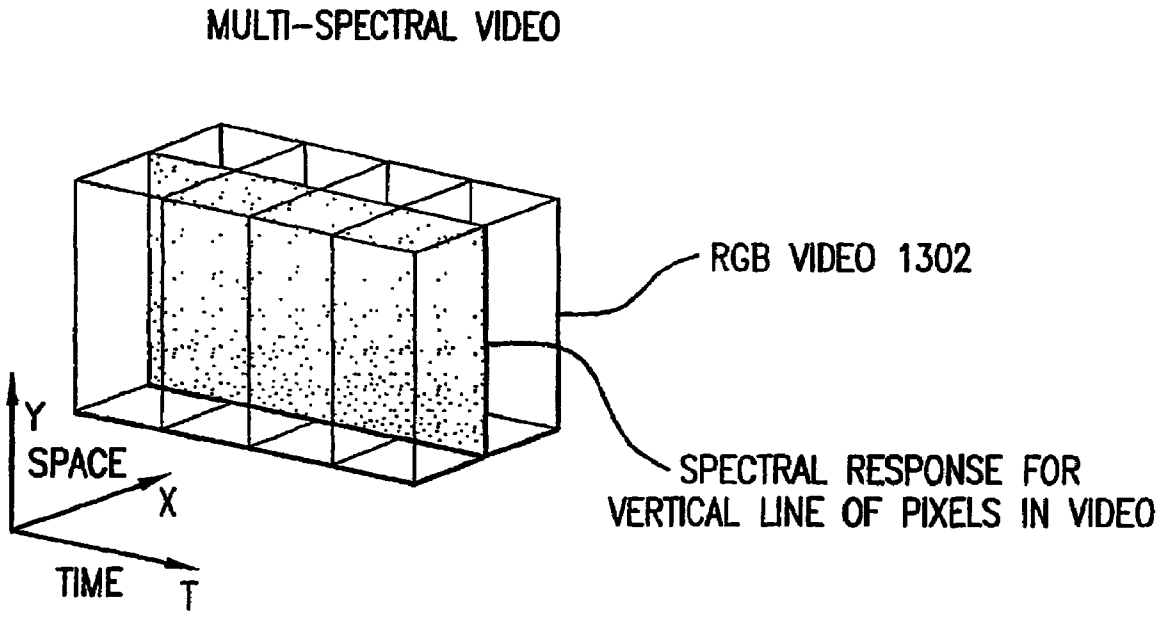

CCD 1214
LENS (1212)
PRISM 1210
LENS 1208
1216
CCD
SLIT 1206
BEAM SPLITTER 1204
DESIGN
930
SPECTROGRAPH OF VERTICAL LINE
VIDEO CAMERA 1202

FIG. 12


MULTI-SPECTRAL VIDEO
RGB VIDEO 1302
SPECTRAL RESPONSE FOR
VERTICAL LINE OF PIXELS IN VIDEO
Y
SPACE
X
TIME
T

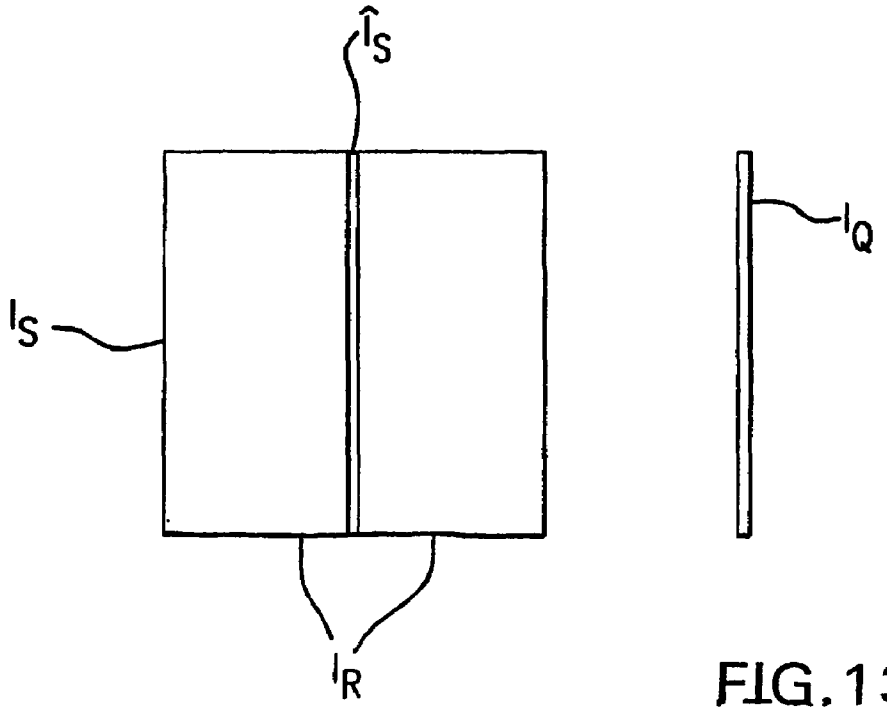

$\hat{I}_S$
I_S
I_Q
I_R

FIG. 13

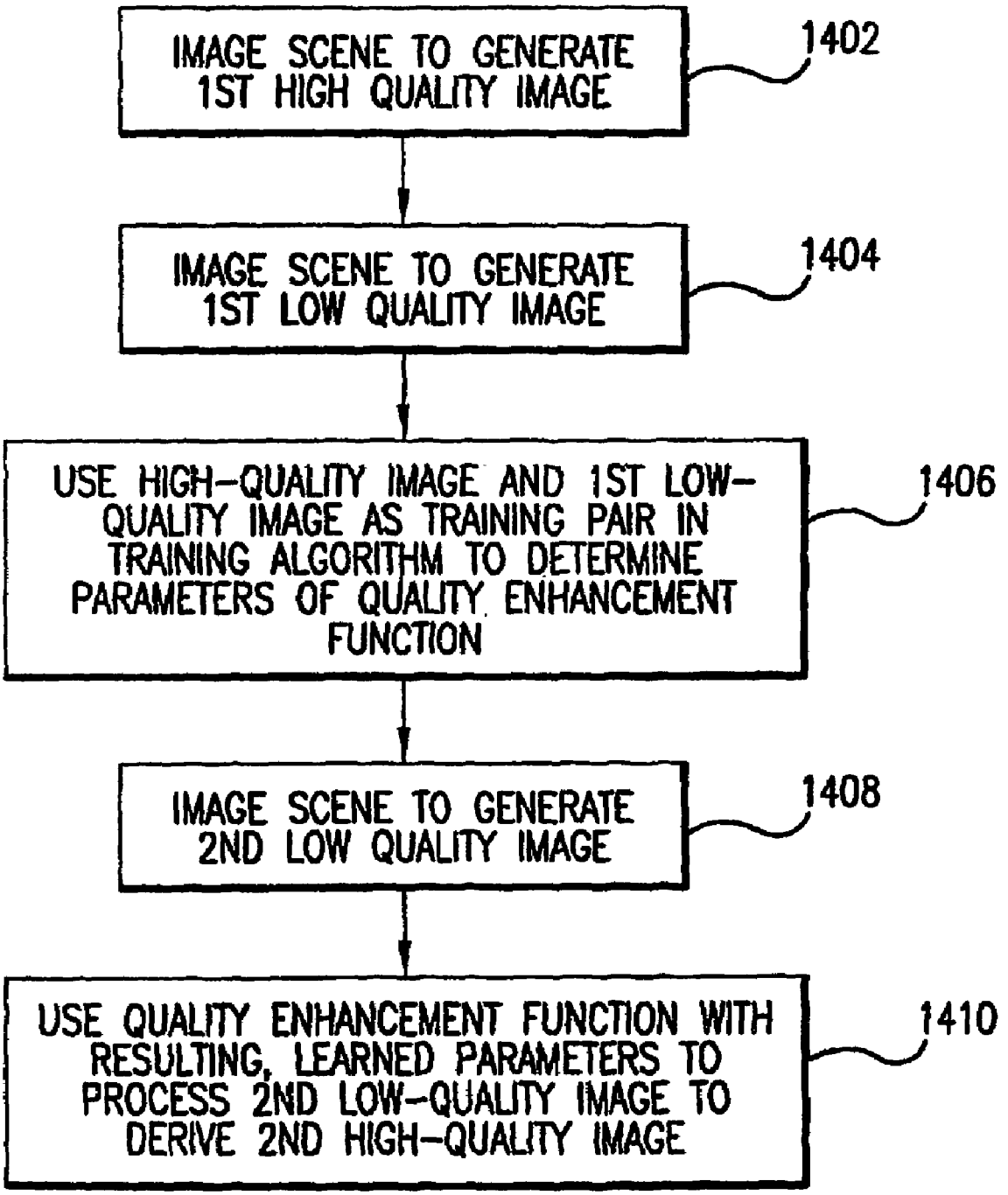


IMAGE SCENE TO GENERATE 1ST HIGH QUALITY IMAGE
1402
IMAGE SCENE TO GENERATE 1ST LOW QUALITY IMAGE
1404
USE HIGH-QUALITY IMAGE AND 1ST LOW-QUALITY IMAGE AS TRAINING PAIR IN TRAINING ALGORITHM TO DETERMINE PARAMETERS OF QUALITY ENHANCEMENT FUNCTION
1406
IMAGE SCENE TO GENERATE 2ND LOW QUALITY IMAGE
1408
USE QUALITY ENHANCEMENT FUNCTION WITH RESULTING, LEARNED PARAMETERS TO PROCESS 2ND LOW-QUALITY IMAGE TO DERIVE 2ND HIGH-QUALITY IMAGE
1410

FIG. 14

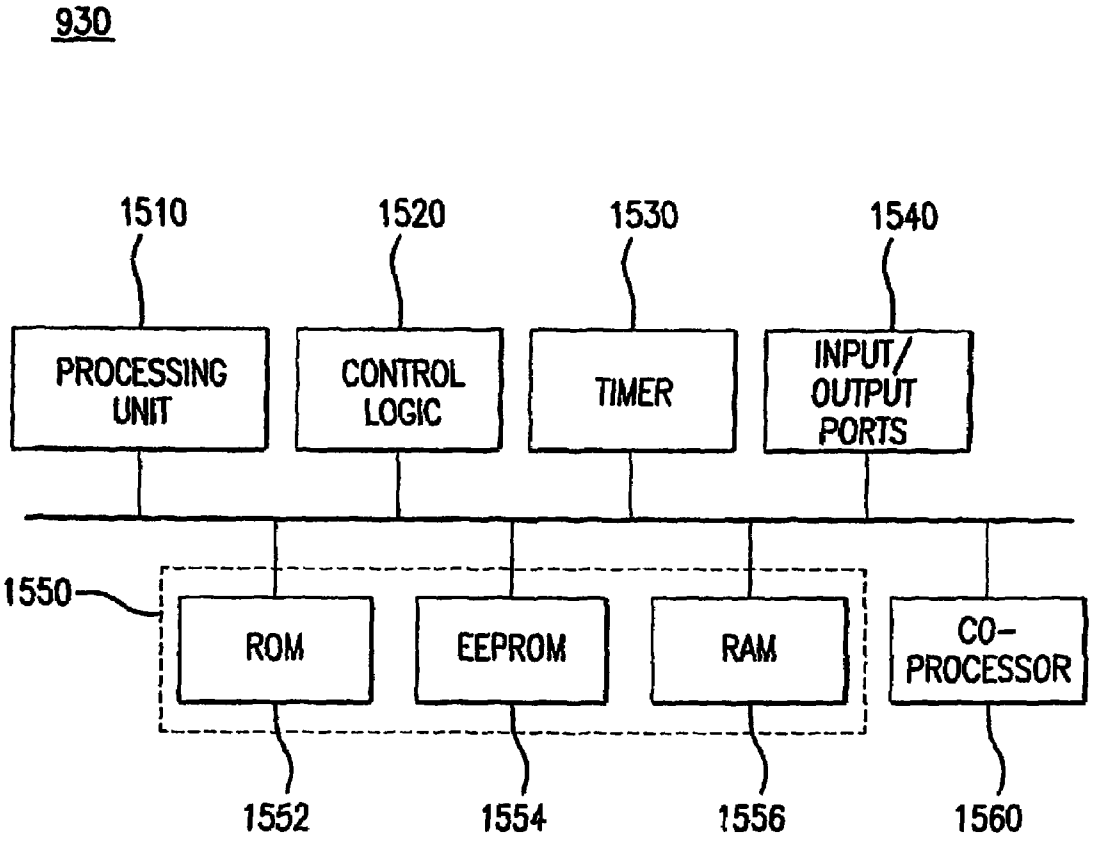

930
1510
1520
1530
1540
PROCESSING UNIT
CONTROL LOGIC
TIMER
INPUT/ OUTPUT PORTS
1550
ROM
EEPROM
RAM
CO-PROCESSOR
1552
1554
1556
1560

FIG.15

METHOD AND SYSTEM FOR ENHANCING DATA QUALITY

CROSS REFERENCE TO RELATED APPLICATION

This application claims priority to U.S. Provisional Patent Application Ser. No. 60/367,324, entitled "Enhanced Imaging Using Self-Training Sensors," filed on Mar. 25, 2002, which is incorporated herein by reference in its entirety.

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH OR DEVELOPMENT

This invention was made with support in part from the U.S. Government under National Science Foundation Research Award No. IIS-00-85864. Accordingly, the U.S. Government may have certain rights in this invention.

BACKGROUND OF THE INVENTION

An imager, such as a video or still camera, images a scene by receiving and detecting light emanating from the scene. The incoming light signal from a particular point in the scene has characteristics, such as an intensity, a wavelength spectrum, and a polarization. In addition, the entire light field received by the imager varies with the angle at which the light is received by the imager. Of course, the angle at which a particular light ray or light ray bundle is received depends upon the location of the scene point from which the light emanated.

A number of applications require precise and accurate measurement of the light field. For example, in Imaged Based Rendering (IBR), a scene is imaged and then re-rendered to simulate navigation around the scene. Measurement of the entire light field with respect to both space and direction allows extraction of the geometric structure of the scene. As another example, light reflected from each material and emanating from each illumination source has its own characteristic spectral curve and polarization characteristics. With high spectral resolution it is possible to identify different types of material and illumination, and/or to re-render the scene under different, simulated illumination. Measuring the polarization of light from a scene point provides further information regarding the type of material present at the scene point, and regarding the illumination incident on the scene point. Polarization information has also been used to compensate for the effects of weather conditions when rendering outdoor scenes, and to help measure depth—i.e., the distance of a scene point from the imager. As can be seen from the above examples, a system which precisely and accurately measures the light field has a variety of useful applications.

However, conventional imagers are limited in their intensity resolution, spectral resolution, and polarization resolution—i.e., their ability to resolve differences in intensity, wavelength, and polarization—and are also limited in their spatial resolution—i.e., their ability to resolve differences in the locations of respective scene points. For example, there currently exist digital still cameras capable of capturing high spatial resolution images. However, because of the amount of data involved, these cameras are not capable of producing high resolution video. On the other hand, inexpensive cameras exist that can capture video at 30 frames/second—a respectable temporal resolution. However, such video cameras provide only low spatial resolution. It is particularly difficult to design an imager having high time resolution and high spatial resolution. In addition to the engineering problems associated with high resolution in multiple dimensions, there are often fundamental physical problems. For example, low light conditions require longer exposure times, resulting in coarser temporal resolution and, accordingly, more blurring in imaging of moving objects.

One approach for addressing the above-described problems uses multiple sensors which are "co-located" (i.e., have the same viewpoint) to measure different aspects of the light field. For example, it is possible to co-locate a thermal imager, a range finder, and a visible-light camera. In some cases a multiple-sensor approach can overcome some of the physical limits imposed on single sensors, such as the trade-off between exposure and temporal resolution. However, such an approach requires additional imaging resources. In a situation in which the available resources are finite—e.g., in which there is a fixed number of pixels, a fixed amount of memory, and trade-offs between exposure and time—it is desirable to use these resources as efficiently as possible.

If the light field were simply an unrelated and arbitrary set of intensities, there would be little hope of a solution other than building bigger, faster, and more densely packed sensors. However, there is tremendous structure and redundancy in the light field. For example, when the viewpoint is shifted slightly, the view of the scene typically changes in predictable ways. In addition, the spectral response across a material of a single color will often be relatively uniform. Furthermore, the motions of objects in a scene are often regular and predictable. For example, most objects are rigid, and in many cases, objects tend to move at nearly constant velocities. All of these factors create great redundancies in the light field. As a result, it is usually not necessary to sample the light field at every point in its domain to reconstruct, approximate, or predict the light field.

To exploit the above-described redundancy in the light field, assumptions can be made regarding the structure of this redundancy. For example, interpolation and sampling theory uses assumptions about the regularity of a signal to recover the signal from a limited number of samples. As a particularly well-known example, the Nyquist theorem states that the maximum required signal sampling frequency is limited, provided that the signal being sampled is band limited—i.e., has frequency components within a finite range. In the context of images, the requirement of finite frequency range essentially translates to a limit on the permissible sharpnesses of discontinuities such as edges and corners. The functions used in the Nyquist theorem are trigonometric functions, but polynomials can also be used for interpolation of images. Simple examples include bilinear and bi-cubic interpolation. Unfortunately, the improvement possible from simple interpolation techniques is limited. In particular, the resolution increases provided by such techniques are typically rather modest. Moreover, since natural images often do not conform to the mathematical assumptions inherent in interpolation techniques, such methods can produce aesthetically unpleasant artifacts.

Sparsely sampling an image and interpolating the resulting data effectively acts as a low-pass filter. Accordingly, increasing the spatial resolution of an image can be expressed as a problem of "de-blurring" the image. Sharpening filters, such as Pseudo Inverse and Weiner Filters, have been used to invert Gaussian blur. Other previously used approaches include Bayesian analysis, interpolation along edges, adaptive filtering, wavelet analysis, fractal interpolation, projection on convex sets, variational methods, and level sets. Such approaches improve on basic

interpolation, but because they only use local image structure or apply a hypothesized global prior to the behavior of the light field—i.e., an assumption regarding the regularity of the light field—their ability to exploit redundancies is somewhat limited.

Related to sampling and interpolation are techniques known as "super-resolution," in which relatively course sampling is performed multiple times to improve the effective resolution of the sampling. As with the above-described interpolation methods, super-resolution makes assumptions about the regularity of the light field, and has recently been shown to have theoretical limits.

Various multi-camera systems have been proposed for capturing light fields over wide areas. Such systems typically use interpolation image warping to fill in missing data. For example, in hybrid imaging, images are captured using multiple cameras with different characteristics—e.g., different frame rates or spatial resolutions. A larger part of the light field is filled in based on computed camera geometry, using a combination of interpolation and image warping.

An additional approach is based on texture synthesis and scene statistics. Rather than make mathematical assumptions about the structure of the redundancy in a light field, statistics or pattern analysis are used to model and exploit the redundancy. One technique uses correlations of pixels at different scales. Another approach is to "train" the model using a variety of different textures and a variety of different images of everyday scenes. In the training approach, the training algorithm should be capable of extracting and utilizing the redundancies in the image to improve the image and increase its resolution. If the domain of image types is very limited—such as in the well-known "hallucinating faces" method, in which high resolution images of human faces are synthesized from low-resolution data—training approaches can dramatically improve resolution. However, attempts to model broader domains typically encounter standard problems of machine learning. For example, if the model is trained on very specific domains, the model becomes over-fitted to the particular training data, resulting in poor generalization. For example, if a resolution-enhancement algorithm is trained on faces and then applied to buildings, the algorithm will tend to produce artifacts and low quality enhancement results. On the other hand, if the model is trained on a very broad domain of image types, it learns only very general redundancies that occur in most images. As a result, although a broadly trained model will provide some benefit for most domains, it will not provide extremely good results for any domain.

SUMMARY OF THE INVENTION

It is therefore an object of the present invention to provide a method and system which enhances the quality of data such as image data (e.g., video and still image data) and sound data while using hardware resources efficiently.

It is a further object of the present invention to provide such data quality enhancement in a manner which avoids undesirable side effects such as visually unpleasing artifacts.

It is a still further object of the present invention to provide data quality enhancement with good performance for a wide variety of different types of images, sounds, etc.

These and other objects are accomplished by a quality enhancement function which is trained on a sub-portion of the data set which will be enhanced. For example, the system can capture low quality image data from an entire scene and high quality image data from a narrow field of view of the scene. The high quality image data—which represents a sub-portion of the scene—and a corresponding sub-portion of the low quality image data—which represents the same sub-portion of the scene—are processed by a training algorithm which trains the quality enhancement function based on these sets of image data. In other words, the quality enhancement function has one or more parameters, and the training algorithm determines which values of these parameters are optimal for allowing the quality enhancement function to derive, from the sub-portion of the low quality data, a data set closely approximating the high quality image. Because the quality enhancement function is trained on high quality and low quality data drawn from the same scene as is represented by the entire low quality image—i.e., the very data that is to be enhanced—the enhancement function is optimized to the most relevant data set. After training, the quality enhancement function is used to enhance the remaining low quality data. The system thus provides the benefits of learning-enhanced imaging without the drawbacks (e.g., poor performance with new domains) associated with conventional systems.

The above-described procedure is not limited to image data, but can also be applied to audio (i.e., sound) data. To enhance a sampled audio signal, a low quality data set representing the signal is captured, along with a high quality data set representing a sub-portion of the same signal. The high quality data set representing the sub-portion of the signal and the corresponding portion of the low-quality data set are processed by a training algorithm which determines optimum, learned values of one or more parameters of a quality enhancement function. The learned parameters are selected such that the quality enhancement function is operable to derive, from the relevant portion of the low quality data set, a data set closely approximating the high quality data set. Once the training has been performed, the quality enhancement function is used to enhance the remaining low quality data.

In accordance with an additional aspect of the present invention, a sequence of images having varying quality can be used to train a quality enhancement function which will then be used to enhance low quality images in the sequence. A high resolution image of a scene and a low resolution image of the same scene are processed by a training algorithm to determine learned values of one or more parameters of a quality enhancement function. The learned values of the parameters are selected such that, with those parameter values, the quality enhancement function is operable to derive from the low quality image an image closely approximating the high quality image. Once the parameters of the quality enhancement function have been learned, the quality enhancement function is used to process additional low quality images of the same scene to derive higher quality images.

BRIEF DESCRIPTION OF THE DRAWINGS

Further objects, features, and advantages of the present invention will become apparent from the following detailed description taken in conjunction with the accompanying figures showing illustrative embodiments of the present invention, in which:

FIG. **1** is a diagram illustrating exemplary image data to be processed in accordance with the present invention;

FIG. **2** is a flow diagram illustrating an exemplary procedure for enhancing quality of image data in accordance with the present invention;

FIG. **3** is a diagram illustrating exemplary sound data to be processed in accordance with the present invention;

FIG. **4** is a block diagram illustrating an exemplary procedure for enhancing quality of image data in accordance with the present invention;

FIG. **5** is a flow diagram illustrating an exemplary procedure for enhancing quality of sound data in accordance with the present invention;

FIG. **6** is a block diagram illustrating an additional exemplary procedure for enhancing quality of sound data in accordance with the present invention;

FIG. **7** is a diagram illustrating exemplary image data to be processed in accordance with the present invention;

FIG. **8** is a diagram illustrating additional exemplary image data to be processed in accordance with the present invention;

FIG. **9**A is a diagram illustrating a system for enhancing quality of image data in accordance with the present invention;

FIG. **9**B is a diagram illustrating an additional system for enhancing quality of image data in accordance with the present invention;

FIG. **9**C is a diagram illustrating yet another system for enhancing quality of image data in accordance with the present invention;

FIG. **10**A is a diagram illustrating a still further system for enhancing quality of image data in accordance with the present invention;

FIG. **10**B is a diagram illustrating yet another system for enhancing quality of image data in accordance with the present invention;

FIG. **11** is a diagram illustrating an exemplary video sequence to be processed in accordance with the present invention;

FIG. **12** is a diagram illustrating a system for generating image data in accordance with the present invention;

FIG. **13** is a diagram illustrating exemplary video and still image data to be processed in accordance with the present invention;

FIG. **14** is a diagram illustrating an exemplary system for enhancing quality of image data in accordance with the present invention; and

FIG. **15** is a block diagram illustrating an exemplary processing arrangement for use in the systems and procedures illustrated in FIGS. **1**–**14**.

Throughout the drawings, unless otherwise stated, the same reference numerals and characters are used to denote like figures, elements, components, or portions of the illustrated embodiments.

DETAILED DESCRIPTION OF THE INVENTION

In accordance with the present invention, data quality can be enhanced by performing low quality and high quality sampling of the same scene or signal to generate data having a low amount of quality as well as corresponding data having a high amount of quality. The low quality data and the corresponding high quality data—which both represent the same portion of the scene or signal—are used to train a data enhancement function which can then be used to enhance the quality of additional low quality data representing the remainder of the scene or the signal. The term "amount of quality" as used herein can, for example, refer to the spatial resolution of data, but need not be limited to spatial resolution. "Quality" can, in fact, be any characteristic related to the precision and/or accuracy with which the data represents a scene, a light field, an audio signal, etc. For example, an amount of quality can be an intensity resolution (e.g., a number of bits per pixel), a spectral resolution (e.g., the number of different spectral components into which light or other radiation has been resolved), a polarization resolution (e.g., how precisely the polarization components of light or other radiation can be resolved), a temporal resolution (e.g., a number of video frames per second or audio samples per second), a signal level resolution (e.g., a number of bits per sample in an audio data stream), and/or a signal-to-noise ratio. An amount of quality can also refer to, for example, the following attributes of an image: the accuracy with which edges appearing in the image represent the actual locations of the edges of objects in a scene, the accuracy with which the image represents the actual colors present in an incoming light field; and/or the accuracy with which the brightness contrast or color contrast of the incoming light field is represented in the image.

FIGS. **2** and **4** illustrate an exemplary procedure for enhancing quality of image data in accordance with the present invention. In the illustrated procedure, a scene is imaged to generate an image of the scene having a low amount of quality (step **202**). A sub-portion of the scene is imaged to generate high-quality image data—i.e., data having a greater amount of quality than the data generated in step **202** (step **204**). Exemplary sets of image data thus generated are illustrated in FIG. **1**. The illustrated data sets include a low spatial resolution, 384×384 pixel image I_S of a wide field of view of the scene, and a high spatial resolution, 256×256 pixel image I_Q of a narrow field of view of the scene. The middle 128×128 pixel subset of I_S, denoted $\hat{I}_S$ (outlined by the white square in the drawing), corresponds to a lower spatial resolution version of high spatial resolution image I_Q. The term "spatial resolution" can, for example, refer to the number of pixels per unit area on a plane at unit depth via perspective projection. Accordingly, although image I_Q has fewer total pixels than image I_S, image I_Q has a higher resolution than I_S. Optionally, low resolution data set $\hat{I}_S$ can be obtained by selecting a portion of the entire low resolution image I_S or by degrading the higher resolution image I_Q to the resolution of the low resolution image I_S. For example, a Gaussian blur kernel for averaging can be applied to the high resolution data, followed by sub-sampling to simulate a low resolution image. A typical Gaussian blur kernel is a square (e.g., 9×9) matrix of elements whose values are based on a normalized, 2-dimensional Gaussian function $G=K\exp((-x^2-y^2)/\sigma^2)$, where K and σ are constants and x and y are the horizontal and vertical coordinates, respectively. An image is blurred by calculating a new value for each pixel, the new value being a weighted average of all of the pixels in a square neighborhood (e.g., a 9×9 neighborhood) surrounding the pixel in question. To calculate the weighted average, each of the values of the respective pixels in the neighborhood is multiplied by the corresponding element of the blur kernel, and the resulting products are added. The resulting sum of the products becomes the new value of the center pixel. Each pixel of the image is individually processed by the above-described procedure to generate a new, blurred image.

The high quality data I_Q and the corresponding subset $\hat{I}_S$ of the low quality image I_S are processed (in step **206**) by a training algorithm **402** to determine learned values **404** of one or more parameters of a quality enhancement function **406**, such that if the learned parameters **404** are used in the quality enhancement function **408**, the function **408** is operable to derive a data set closely approximating the high quality data I_Q from the subset $\hat{I}_S$ of the low-quality data I_S. Once the appropriate parameters of the quality enhancement function are learned, the resulting, optimized function can be

used to process the remainder I_R of the low quality data set I_S to derive a data set I_R' representing the remainder of the scene (step **208**). The high quality data sets I_Q and I_R' can be combined (step **408**) to derive a high quality image I_H of the entire scene.

Optionally, the low resolution data subset $\hat{I}_S$ and the high resolution data set I_Q can be processed by selecting one or more "training pairs"—small portions taken from a variety of different regions in the sets of image data. FIG. **7** illustrates a number of training pairs that can be extracted from the low resolution and high resolution image data sets $\hat{I}_S$ and I_Q illustrated in FIG. **1**. The low resolution, 5×5 pixel image patches P_{S1}, P_{S2}, P_{S3}, and P_{S4} illustrated in FIG. **7** have been taken from $\hat{I}_S$, and the corresponding high resolution, 10×10 pixel patches P_{Q1}, P_{Q2}, P_{Q3}, and P_{Q4} have been taken from I_Q. The resulting pairs of image patches—(P_{S1}, P_{Q1}), (P_{S2}, P_{Q2}), (P_{S3}, P_{Q3}), and (P_{S4}, P_{Q4})—provide the training data for the training algorithm **402**.

The quality enhancement function **406** is trained (in training algorithm **402**) by applying polynomial regression to a set of training pairs (P_{S1}, P_{Q1}), . . . , (P_{SK}, P_{QK}), where K represents the number of training pairs. First, the training algorithm **402** arranges the values of the 25 pixels of each low resolution patch P_{Sn} to form a 25-element row vector W_{Sn}. The values of the 25 pixels can be arranged in any convenient order, but the same order is used for all patches. The vectors of the respective patches are then arranged into a matrix $W_S:=(W_{S1}{}^T, \ldots, W_{SK}{}^T)^T$ (where "T" denotes the transpose of a vector or matrix). If W_{S1} is the vector representing the first low resolution, 5×5 patch P_{S1}, then let z_i (W_{S1}) (where i=1, . . . 25) represent the value of ith pixel of that patch P_{S1}. In order to improve the efficiency of the training algorithm **402**, the algorithm **402** preferably only considers degree-2 polynomials. Accordingly, let t be a list or vector of all the degree-2 and smaller monomials, including: (a) the value 1; (b) the values of the respective pixels; and (c) all possible degree-2 monomials that can be formed by multiplying the various pixels of the patch P_{S1} with each other and with themselves:

$$t\equiv(t_1 \ldots, t_p)\equiv(1,z_1, \ldots, z_{25},z_1{}^2,z_1z_2, \ldots, z_{25}{}^2). \quad (1)$$

For each low resolution patch, a row vector of these monomials is formed. For example, the row vector corresponding to patch P_{S1} is $t(W_{S1}):=(t_1(W_{S1}), \ldots t_P(W_{S1}))$. If, as is illustrated in FIG. **8**, the patch P_{S1} has 25 pixels, the corresponding row vector $t(W_{S1})$ has 651 elements. The row vectors for the respective patches are arranged into a matrix:

$$t(W_S)\equiv(t(W_{S1})^T, \ldots t(W_{SK})^T)^T. \quad (2)$$

In the illustrated example, 4:1 enhancement of spatial resolution is being performed. Accordingly, each low resolution pixel in a given low resolution patch corresponds to four high resolution pixels in the corresponding high resolution patch. For example, as is illustrated in FIG. **8**, pixel **802** in the 5×5 patch P_{S1} corresponds to four pixels **804**, **806**, **808**, and **810** in locations a, b, c, and d, respectively, within the corresponding high resolution patch P_{Q1}—each of the locations a, b, c, and d being defined in relation to the location of the pixel **802** in the middle of the low resolution patch P_{S1}. The values of high resolution pixels **804**, **806**, **808**, and **810** can be denoted mathematically as $(W_{Q1})_a$, $(W_{Q1})_b$, $(W_{Q1})_c$, and $(W_{Q1})_d$, respectively. In the illustrated example, only the four middle pixels, **804**, **806**, **808**, and **810** of the high resolution patch P_{Q1} are used for training; the remaining pixels of the high resolution patch P_{Q1} need not be used. Each function of a set of quality enhancement functions being trained will ultimately be used to operate on an entire low resolution patch—which can be viewed as a neighborhood of the pixel in the middle of the patch—to derive one of the four high resolution pixels which will replace the aforementioned low resolution pixel in middle of the neighborhood. For example, in the case of 4:1 spatial resolution enhancement based on a 5×5 low resolution neighborhood/patch, each of four separate resolution enhancement functions f_a, f_b, f_c and f_d operates on the entire low resolution patch to derive one of the four corresponding high resolution pixels in the four pixel locations a, b, c, and d. The training algorithm **402** operates on the principle that, if the quality enhancement functions f_a, f_b, f_c and f_d are properly optimized—i.e., if the coefficients of the functions are properly chosen—it should be possible to accurately derive a given high resolution pixel (e.g., pixel **804**) from the values of all of the pixels in the low resolution patch (e.g., P_{S1} illustrated in FIG. **8**). The coefficients for a given pixel m (where m=a, b, c, or d) form a row vector $C_m=(c_{m1}, \ldots, c_{mK})^T$, wherein the values of the coefficients in C_m depend on which high quality pixel is being derived—i.e., whether the pixel being derived is in location a, b, c, or d. In other words, each of the four high quality pixel locations a, b, c, and d has a different set of coefficients: C_a, C_b, C_c, and C_d, respectively, for functions f_a, f_b, f_c and f_d. Preferably, multiple training pairs are used, each having a low resolution patch and four corresponding high resolution pixels in locations a, b, c, and d, respectively. Using the values—taken from all of the training pairs—that are associated with a given pixel location m, the values of the respective high quality pixels situated at that pixel location m can be arranged into a vector:

$$(W_Q)_m=((W_{Q1})_m, \ldots, (W_{QK})_m)^T \quad (3)$$

for m=a, b, c, and d. For any one of these four pixel locations—i.e., for any given m—C_m should solve the following matrix equation:

$$t(W_S)C_m=(W_Q)_m, \quad (4)$$

provided that the coefficients of C_m have been correctly determined. Several well known linear algebra techniques exist for finding a solution to vector C_m in matrix equations having the form of Eq. (4). For example, if $t(W_S)^Tt(W_S)$ is invertible, then the training algorithm **402** can compute C_m as follows:

$$C_m=(t(W_S)^T(W_x))^{-1}t(W_S)^T(W_Q)_m. \quad (5)$$

Eq. (5) provides the least squares solution for C_m in Eq. (4)—i.e., provides the set of vector element values for C_m that minimizes the sum of square differences between the left and right sides of Eq. (4).

In this example, the outputs of the learning phase are the four coefficient vectors C_a, C_b, C_c, and C_d. These vectors C_a, C_b, C_c, and C_d thus contain the coefficients of the four polynomial enhancement functions f_a, f_b, f_c and f_d, respectively, that can operate on any given 5×5 low resolution patch L to derive the four corresponding high resolution pixels H_m in the middle of the neighborhood of that patch L, where:

$$H_m=f_m'(L)\equiv t(L)C_m \quad (6)$$

for m=a, b, c, and d. To enhance a low resolution image data set or subset, such as image subset I_R illustrated in FIG. **1**, the enhancement algorithm (step **208** in FIG. **2**) typically starts by processing a first 5×5 patch L of the data set I_R (e.g., the patch L in the upper left corner, as illustrated in FIG. **1**)

to generate the four high resolution pixels H_a, H_b, H_c, and H_d in the center of the corresponding neighborhood of high resolution image data set I_R'. The algorithm then processes the next patch by shifting over (e.g., to the right) by one low-resolution pixel to generate the adjacent set of four high resolution pixels. In other words, there is preferably an overlap area of, e.g., 4×5 pixels between the successive low resolution patches being processed, thus ensuring full coverage of the scene area in the resulting high resolution image data set I_R'. This overlap should exist in both the vertical and horizontal directions.

It is to be noted that, although the above discussion has emphasized the processing of data sets having different spatial resolutions, the procedures illustrated in FIGS. **2** and **4** can also be used to process data sets having different intensity resolutions (e.g., different numbers of gray levels and/or bits per pixel). Referring again to FIGS. **1**, **2**, and **4**, if the low quality image I_S is an image having low intensity resolution, and the high resolution image I_Q is an image having high intensity resolution, the high resolution image I_Q and the first subset $\hat{I}_S$ of the low resolution image I_S—both of which represent the same portion of the scene—are processed by a training algorithm **402** (step **206**) to determine the parameters **404** of a quality enhancement function **406**. The quality enhancement function **406** has thus been optimized and can therefore be used to enhance the resolution of the remaining subset I_R of the low intensity resolution image I_S to derive a high intensity resolution image I_R' of the remainder of the scene (step **208**). The high resolution images I_Q and I_R' can then be combined (step **408**) to provide an improved image I_H of the entire scene, which has higher intensity resolution than the initially captured low quality image I_S of the scene.

FIG. **9**A illustrates an exemplary system for collecting high and low quality data for enhancement in accordance with the present invention. The illustrated imaging system includes a first imager **902** having a relatively wide field of view **908** but relatively low quality (e.g., low spatial or intensity resolution), a second imager **904** having a narrower field of view **910** but high quality (e.g., high spatial or intensity resolution), and a beam splitter **906**. The beam splitter **906** directs the incoming light to both the low quality imager **902** and the high quality imager **904**, and these imagers **902** and **904** can be used to generate the low resolution image I_S and the high resolution image I_Q illustrated in FIG. **1**. Optionally, the system can also include a processing arrangement **930**—which can comprise, for example, a computer or special-purpose processing logic—for performing the data enhancement procedures discussed above with respect to FIGS. **1**, **2**, and **4**. Alternatively, or in addition, the processing arrangement **930** can be incorporated into one or both of the imagers **902** and **904**.

FIG. **9**B illustrates an additional exemplary system for generating image data for use in the training algorithm and quality enhancement procedure discussed above. The illustrated system includes a camera **912** and a curved mirror **920** which provides a wide angle view of the scene. The mirror **920**—which can be, for example, a parabolic mirror—provides a low resolution field of view **914**, a high resolution field of view **918**, and an intermediate resolution field of view **916**. The data collected from the high resolution field of view **918** and/or the intermediate resolution field of view **916** can be degraded to provide low resolution training data for use in conjunction with the originally captured high and medium resolution data. Optionally, a processing arrangement **930**—as discussed above with respect to FIG. **9**A—can be incorporated into the camera **912**.

FIG. **9**C illustrates an additional example of a multi-resolution imaging system. The imaging system comprises a camera **922** having a CCD array **924** with a low resolution portion **928** and a high resolution portion **926**. The high resolution portion **926** captures data within a high resolution field of view **910**, whereas the low resolution portion **928** captures data from a low resolution field of view **908**. Although the imager **922** does not directly capture low resolution data from the high resolution portion **910** of its field of view, the high resolution data collected from that portion **910** of the field of view can be downgraded as described above to derive low resolution training data for use in conjunction with the high resolution data collected by the high resolution portion **926** of the CCD array **924**.

It is to be noted that, although the foregoing examples have emphasized the use of a training algorithm based on polynomial regression, the technique of training on low resolution data and high resolution data from the same scene is not limited to such a training algorithm. In fact, any training algorithm which uses regression to adjust the parameters of a data quality enhancement function can be used. Additional examples of suitable algorithms include the following well known training algorithms which will be familiar to those skilled in the art: Bayesian Decisions, Maximum Likelihood, Linear Discriminants, Neutral Networks, Genetic Programming, and Kernel Methods such as Support Vector Machines.

A quality enhancement procedure in accordance with the present invention can also be used to enhance sound/audio data, as is illustrated in FIGS. **3**, **5**, and **6**. In the illustrated procedure, a sound signal is detected to generate a set A_S of low quality sound data (step **502**). The low quality data set A_S includes first and second portions $\hat{A}_S$ and A_R—e.g., data collected from time t_1 to time t_2, and data collected from time t_2 to time t_3. A set A_Q of high quality sound data is generated by sampling the same sub-portion of the sound signal that is used to generate the first low quality data subset $\hat{A}_S$ (step **504**). For example, the sound signal can be sampled at 22 kHz to derive the low quality data set A_S (including subsets $\hat{A}_S$ and A_R) and at 44 kHz to generate the high quality sound data set A_Q. Alternatively, or in addition, the first subset $\hat{A}_S$ of the low quality data set A_S can be derived by degrading the high quality data A_Q—e.g., by deleting one of every two samples. The quality of the sound data can also be defined by the signal level resolution—e.g., the number of bits per sample. For example, the low quality data can have 8 bits per sample and the high quality data can have 16 bits per sample.

In any case, the high resolution sound data A_Q and the first subset of $\hat{A}_S$ of low resolution sound data are used as a training pair for a training algorithm **602** to derive optimized parameters **604** of a quality enhancement function **606** (step **506**). For example, if the quality enhancement function **606** is a polynomial function, polynomial coefficients vectors C_a, C_b, C_c, etc. are derived by the training algorithm **602**. In any case, once the learned parameters **604** of the quality enhancement function **606** have been determined, the quality enhancement function, with the learned parameters, is used to process the second subset A_R of low quality sound data to derive high quality sound data A_R' representing the remainder of the sound signal (step **508**). The high quality sound data A_R' thus derived can be combined with the high quality, sampled sound data A_Q (step **608**) to derive a complete set of high quality sound data A_H representing the entire sound signal.

In accordance with an additional aspect of the present invention, a quality enhancement function can be trained on

a set of video frames having different amounts of quality—e.g., different spatial resolutions—as is illustrated in FIGS. **11** and **14**. In the illustrated procedure, a scene is imaged to generate a first high quality image **1102** (e.g., a high quality video frame) (step **1402**). The scene is imaged again to generate a first low quality image/video frame **1104** (step **1404**). The high quality image **1102** and the first low quality image **1104** are used as a training pair in a training algorithm such as is discussed above to determine the parameters of a quality enhancement function (step **1406**). When one or more additional low resolution frames (e.g., low quality image **1106**) are generated (step **1408**), the quality enhancement function can be used with the learned parameters to process the additional low quality images to derive an additional high quality images (step **1410**). It is to be noted, however, that although FIG. **14** illustrates the above-described procedure as applying the training algorithm before the additional low quality images are captured, the training algorithm can just as easily be applied after all or most of the image data has been captured.

FIGS. **10**A and **10**C illustrate exemplary systems for generating image data for use in the procedure illustrated in FIG. **14**. The system illustrated in FIG. **10**A includes a high resolution video camera **1002**, a low resolution video camera **1004**, and a beam splitter **1006** to distribute the incoming light to the two cameras **1002** and **1004**. Because the same incoming beam is imaged by both cameras **1002** and **1004**, the system can be considered to have a single viewpoint **1014**. Optionally, the high resolution camera **1002** can have a low frame rate, and the low resolution camera **1004** can have a high frame rate. For example, the high resolution camera **1002** can produce video data with a spatial resolution of 1000×1000 pixels and a frame rate of 3 frames per second, and the low resolution video camera **1004** can produce video data with a spatial resolution of 500×500 pixels and a frame rate of 30 frames per second.

Similarly to the system illustrated in FIG. **10**A, the system illustrated in FIG. **10**C includes a high resolution video camera **1002** and a low resolution video camera **1004**. However the system illustrated in FIG. **10**C does not include a beam splitter **1006**. Rather, the two cameras **1002** and **1004** illustrated in FIG. **10**C have different viewpoints **1012** and **1014**, respectively. Preferably, the viewpoints **1012** and **1014** of the cameras **1002** and **1004** are proximate—in particular, the viewpoints **1012** and **1014** are preferably sufficiently close together compared to the depth of the scene being imaged that little or no parallax adjustment is required. The procedure illustrated in FIG. **14** is used to process the low resolution and high resolution images generated by the cameras **1002** and **1004** (the images having been generated in steps **1402** and **1404** illustrated in FIG. **14**) to train the resolution enhancement function discussed above (step **1406**), whereupon further low resolution images generated by the low resolution camera **1004** (step **1408**) are enhanced by the optimized quality enhancement function to derive high quality images (step **1410**). The viewpoint of the enhanced resolution images is typically equal or proximate to the viewpoint **1014** of the low resolution camera **1004** used to generate the low resolution images from which the enhanced resolution images are derived.

FIG. **10**B illustrates a CCD array **1008** suitable for generating image data for use in the procedure illustrated in FIG. **14**. The illustrated CCD array **1008** can be used to generate data at varying resolutions by clustering individual elements (e.g., into groups of 4 pixels) to form "super pixels" 1010. The 4 pixels in each super pixel **1010** can, for example, be clustered by averaging the values of the 4 pixels. Such clustering of pixels is advantageous because, although the spatial resolution of the devices is reduced, clustering allows the CCD array **1008** to sample at a higher frame rate. The pixels need not be clustered for every frame. The resolution of successive frames can be varied—for example, by capturing a sequence of nine low resolution images at a high frame rate, followed by one high resolution image. By using the high resolution image and one or more of the low resolution images to train a quality enhancement function, as is discussed above with respect to FIGS. **11** and **14**, the low resolution images can be enhanced to derive high resolution images. As a result, the system is able to generate high resolution video at a high frame rate.

In accordance with the present invention, the spectral resolution of image data can also be enhanced. FIG. **12** illustrates a system for generating image data having portions with high spectral resolution and portions with low spectral resolution. The system includes a video camera **1202**, a beam splitter **1204**, a slit **1206**, a first lens **1208**, a prism **1210**, a second lens **1212**, and a CCD array **1214**. The beam splitter **1204** passes some of the incoming light through to the video camera **1202** and redirects the remaining light toward the slit **1206**, from which a narrow beam **1216** of light passes through the first lens **1208** and into the prism **1210**. The prism **1210** directs the various spectral components of the beam in different directions. The components pass through the second lens **1212** and are received and detected by the CCD array **1214**. The resulting output of the CCD array **1214** is a high spectral resolution measurement of the wavelengths present in the narrow beam of light **1216** passing through the slit **1206**. Even if the video camera **1202** is a color video camera, such a camera typically provides only coarse red, green, and blue (RGB) information. In contrast, because the light received by the CCD array **1214** has passed through a slit **1206** and a prism **1210**, the various wavelengths present in the light have been spread horizontally across the entire CCD array **1214**. The resulting spectral information includes measurements of as many spectral components as the number of pixels across the horizontal dimension of the CCD array **1214**. FIG. **13** illustrates exemplary video data generated by the system illustrated in FIG. **12**. In each frame of the video data, there is a low quality (in this case, low spectral resolution) image I_S which has been generated by the camera **1202** and which includes a first data subset $\hat{I}_S$ and a second data subset I_R. Also included is a high quality (in this case, high spectral resolution) data set I_Q which has been generated by the CCD array **1214** and which represents the same portion of the scene as the first subset $\hat{I}_S$ of the low resolution data set I_S. Similarly to the image data I_S and I_Q illustrated in FIG. **1**, the image data I_S and I_Q illustrated in FIG. **13** can be processed—e.g., by processing arrangement **930** illustrated in FIG. **12**—according to the training and quality enhancement procedure illustrated in FIGS. **2** and **4** to derive an image representing the entire scene, but having a far greater amount of spectral information than is present in the low quality image I_S. Optionally, a video sequence of **1302**—with each frame of the sequence **1302** including low spectral resolution data I_S and high spectral resolution data I_Q—can be captured and enhanced to derive a video sequence representing the entire scene with high spectral resolution.

It will be appreciated by those skilled in the art that the methods and systems illustrated in FIGS. **1**–**14** can be implemented on various standard processing arrangements operating under the control of suitable software defined by FIGS. **1**–**8**, **11**, **13**, and **14**. FIG. **15** is a functional block

diagram illustrating exemplary processing hardware **930** suitable for performing the methods of the present invention. Such a processing arrangement **930** can optionally be incorporated into one or more of the above-described imagers used to generate image data—as is illustrated in FIGS. **9**B and **9**C—or can be a separate device—as is illustrated in FIGS. **9**A and **12**. The illustrated arrangement **930** generally includes a processing unit **1510**, control logic **1520**, and a memory unit **1550**. Preferably, the processing arrangement also includes a timer **1530** and input/output ports **1540**. The arrangement can also include a co-processor **1560**, depending on the microprocessor used in the processing unit **1510**. Control logic **1520** provides, in conjunction with processing unit **1510**, the control necessary to handle communications between memory unit **1550** and input/output ports **1540**. Timer **1530** provides a timing reference signal for processing unit **1510** and control logic **1520**. Co-processor **1560** provides an enhanced ability to perform complex computations in real time, such as those required by cryptographic algorithms.

Memory unit **1550** can include different types of memory, such as volatile and non-volatile memory and read-only and programmable memory. For example, as is illustrated in FIG. **15**, memory unit **1550** can include read-only memory (ROM) **1552**, electrically erasable programmable read-only memory (EEPROM) **1554**, and random-access memory (RAM) **1556**. Different processors, memory configurations, data structures and the like can be used to practice the present invention, and the invention is not limited to a specific platform.

Software defined by FIGS. **1**–**8**, **11**, **13**, and **14** can be written in a wide variety of programming languages, as will be appreciated by those skilled in the art. For example, software algorithms in accordance with the present invention have been written in the programming language of the well known MATLAB® mathematics tool. The source code for exemplary algorithms written in the MATLAB® language is provided in Appendices A,B, and C attached hereto.

It is to be noted that although the foregoing descriptions of image enhancement have emphasized the imaging of scenes as viewed within the visible light spectrum, the disclosed techniques are applicable to imaging of any form of radiation, including, but not limited to, ultraviolet, infrared, X-ray, radar, ultrasound, etc.

Although the present invention has been described in connection with specific exemplary embodiments, it should be understood that various changes, substitutions, and alterations can be made to the disclosed embodiments without departing from the spirit and scope of the invention as set forth in the appended claims.

Appendix A

MATLAB® Source Code of Exemplary Algorithm for Computing Vector t of Degree-2 Monomials

```
% In this version the "t" function is computed
% but terms such as z1*z2 are ignored, only terms
% such as z1^2, z2^2, are considered. This
% improves efficiency although gives
% a less accurate approximation
function fsVect = nbhdToFS(a,nbhd,degree)
% No-cross terms
nV = nbhd(:);
nLen = prod(size(nV));
fsVect = zeros(nLen*degree,1);
fsVect(1:nLen) = nV;
for deg = 2:degree
    fsVect((((deg-1)*nLen)+1):(deg*nLen)) = . . .
        nbhd(:).* . . .
        fsVect((((deg-2)*nLen)+1):((deg-1)*nLen));
end
```

Appendix B

MATLAB® Source Code of Exemplary Learning/Training Algorithm

```
% This is matlab source code for learning
% the coefficients for enhancement
% polyLearnedModel constructor
function a = polyLearnedModel(fctr,nbhdSize,degree,1rSeq,hr,Seq)
a.null = '';
if 0 == nargin
    %Create a dummy model
    a.fctr = 0;
    a.nbhdSize = [1,1];
    a.degree = -1;
    a.params = [ ];
    b = enhancementModel('polyLearnedModel',[1,1]');
    a = class(a,'polyLeamedModel',b);
elseif 1 == nargin
    if isa(fctr,'polyLearnedModel');
        a = fctr;
    else
        errstr = [num2str(fctr), . . .
            'Not polyLearnedModel object'];
        error(errstr);
    end
elseif 5 == nargin
    a.fctr = fctr;
    a.nbhdSize = nbhdSize;
    a.degree = degree;
    a.params = [ ];
    dummy = polyLeamedModel;
    params = interpKernel(fctr,nbhdSize,degree,1rSeq,hrSeq,dummy);
    b = enhancementModel('polyLearnedModel',params);
    a.params = params;
    a = class(a,'polyLearnedModel',b);
else
    error('Argument wrong type')
end
return
function kern Vals = . . .
    interpKernel(fctr,nSize,degree,1rSeq,hrSeq,modl)
 % A variable to allow for normalization and subtraction of the DC
component
 %DCSUB = 0;
epsilon = 2^(-26);
%epsilon = 0
1rSeqSize = size(1rSeq);
hrSeqSize = size(hrSeq);
if prod((fctr*1rSeqSize) == hrSeqSize) & (2 == length(1rSeqSize))
    ; % Ok
 elseifprod((fctr*1rSeqSize(1:2)) == hrSeqSize(1:2)) & . . .
        (length(1rSeqSize) <=3 )
    ; % Ok
else
    error('Images sequences improper sizes with respect to fctr')
end
% 'in polyLearnedModel Constructor fvSize'
    fvSize = size(nbhdToFS(modl,zeros(nSize),degree));
    featVectLen = prod(fvSize);
    fvMat = zeros([featVectLen,featVectLen]);
    outMat = zeros([featVectLen,fctr^2]);
    inRows = 1:(1rSeqSize(1)-(nSize(1)+1))
```

-continued

```
    inCols = 1:(1rSeqsize(2)−(nSize(2)+1));
    nRad = floor((1/2)*nSize);
    hrOffset = (fctr*(nRad−(~mod(nSize,2)))) + . . .
        (~mod(nSize,2)).*[fctr/2,fctr/2]+1;
    if (length(1rSeqSize) <3)
        numIms = 1;
    elseif (3==length(1rSeqSize) )
        numIms = 1rSeqSize(3);
    else
        error('Images sequences improper sizes')
    end
    for imInd = 1:numIms
        if (length(1rSeqSize) <3)
            1rIm = 1rSeq;
            hrIm = hrSeq;
        elseif (3==length(1rSeqSize))
            1rIm = 1rSeq(:,:,imInd);
            hrIm = hrSeq(:,:,imInd);
        end
        for inR = inRows
            for inC = inCols
                inN = getNbhd(inR,inC,1rIm,nSize);
                featVect =nbhdToFS(modl,inN,degree);
                fvMat = fvMat + featVect * featVect';
                out = fctr * [(inR−1),(inC−1)] + hrOffset;
                outN = getNbhd(out(1),out(2),hrIm,[fctr,fctr]);
                outMat = outMat + featVect*outN(:)';
        end
    end
end
'cond'
cond(fvMat)
'rank'
rank(fvMat)
'size'
size(fvMat)
if (abs(max(fvMat(:))) > epsilon) | . . .
        (abs(min(fvMat(:))) > epsilon)
    % Solving Using SVD
    [U,S,V] = svd(fvMat);
    % We have to kill the eigenvalues that are really close to zero
    nz = (abs(S)>epsilon);
    invS = (ones(size(nz))./(~nz)+S)).*nz;
    kernVals = V*invS*U*outMat;
else
    % Very singular fvMat
    kemVals = zeros(featVectLen,fctr^2);
end
return
% ['',num2str( )]
function inNbhd = getNbhd(iR,iC,im,inNbhdSize)
    indsR = (iR−1)+(1:inNbhdSize(1));
    indsC = (iC−1)+(1:inNbhdSize(2));
    inNbhd = im(indsR,indsC);
    return
```

Appendix C

MATLAB® Source Code of Exemplary Algorithm for Enhancing Image Resolution Using Learned Coefficients

```
    function newIm = improveImage(modl,im)
    nSize = modl.nbhdSize;
    imSize = size(im);
    fctr = modl.fctr;
    if (nSize(1) > imSize(1)) | (nSize(2) > imSize(2))
        error('Neighborhood larger than image.')
    end
    nbhdRad = floor((1/2)*nSize);
    eImSize = fctr * (imSize − nSize+ones(size(nSize)));
    newIm = zeros(eImSize);
```

-continued

```
    nbhdsRow = 1:(imSize(1) − nSize(1)+1);
    nbhdsCo1 = 1:(imSize(2) − nsize(2)+1);
    nbhdRInds = 0:(nSize(1)−1);
    nbhdCInds = 0:(nSize(2)−1);
    for nR = nbhdsRow
        for nC = nbhdsCo1
            nbhd=im(nR+nbhdRInds,nC+nbhdCInds)
            newValues = nbhdFunc(nbhd,mod1);
            newBlock = reshape(newValues,[fctr,fctr]);
            newIm(fctr*(nR−1)+(1:fctr), . . .
                fctr*(nC−1)+(1:fctr)) = newBlock;
        end
    end
    return;
    function newVals = nbhdFunc(nbhd,modl)
        %DCSUB = 0;
        nSize = size(nbhd);
        degree = get(modl,'degree');
        fsVect = nbhdToFS(modl,nbhd,degree);
        newVals = ((fsVect)*(modl.params))';
        return
```

We claim:

1. A method for enhancing data quality using a first data set, a second data set, and a quality enhancement function having at least one parameter, the first data set representing at least one of a scene and a signal, the second data set representing a first sub-portion of the at least one of the scene and the signal, the first data set having a first amount of quality, the second data set having a second amount of quality, the second amount of quality being greater than the first amount of quality, the first data set including first and second data subsets, the first data subset representing the first sub-portion of the at least one of the scene and the signal, the second data subset representing a second sub-portion of the at least one of the scene and the signal, each of the first and second data subsets having the first amount of quality, the method comprising:

processing the first data subset and the second data set by a training algorithm to determine a respective learned value of each one of the at least one parameter, wherein the quality enhancement function is operable to derive, based on the first data subset and using the respective learned value of each one of the at least one parameter, a data set approximating the second data set; and

processing the second data subset by the quality enhancement function using the respective learned value of each one of the at least one parameter to derive a third data set, the third data set representing the second sub-portion of the at least one of the scene and the signal, the third data set having a third amount of quality, the third amount of quality being greater than the first amount of quality.

2. A method according to claim **1**, wherein the first amount of quality comprises a first resolution, the second amount of quality comprising a second resolution, the third amount of quality comprising a third resolution.

3. A method according to claim **2**, wherein the at least one of the scene and the signal comprises the scene, the first resolution comprising at least one of a first spatial resolution, a first intensity resolution, a first spectral resolution, and a first polarization resolution, the second resolution comprising at least one of a second spatial resolution, a second intensity resolution, a second spectral resolution, and a second polarization resolution, the third resolution comprising at least one of a third spatial resolution, a third intensity resolution, a third spectral resolution, and a third polarization resolution.

4. A method according to claim 2, wherein the first resolution comprises a first temporal resolution, the second resolution comprising a second temporal resolution, the third resolution comprising a third temporal resolution.

5. A method according to claim 2, wherein the at least one of the scene and the signal comprises the signal, the first resolution comprising at least one of a first signal level resolution and a first temporal resolution, the second resolution comprising at least one of a second signal level resolution and a second temporal resolution, the third resolution comprising at least one of a third signal level resolution and a third temporal resolution.

6. A method according to claim 1, wherein the first amount of quality comprises a first signal-to-noise ratio, the second amount of quality comprising a second signal-to-noise ratio, the third amount of quality comprising a third signal-to-noise ratio.

7. A method according to claim 1, wherein the first amount of quality comprises a first accuracy, the second amount of quality comprising a second accuracy, the third amount of quality comprising a third accuracy.

8. A method according the claim 1, wherein the quality enhancement function comprises a polynomial function, the at least one parameter comprising one or more coefficients of the polynomial function.

9. A method according to claim 8, wherein the training algorithm comprises determining a respective value of each of the one or more coefficients which minimizes a sum of square differences between the second data set and the data set approximating the second data set.

10. A method according to claim 1, wherein the training algorithm comprises determining a respective value of each one of the at least one parameter which minimizes a sum of square differences between the second data set and the data set approximating the second data set.

11. A method for enhancing data quality using a high quality image data set representing a scene, a first low quality image data set representing the scene, a second low quality image data set representing the scene, and a quality enhancement function having at least one parameter, an image corresponding to the high quality image data set having a first amount of quality, images corresponding to the first and second low quality image data sets having a second amount of quality, the first amount of quality being greater than the second amount of quality, the method comprising:

processing the high quality image data set and the first low quality image data set by a training algorithm to determine a respective learned value of each one of the at least one parameter, wherein the quality enhancement function is operable to derive, based on the first low quality image data set and using the respective learned value of each one of the at least one parameter, an image data set approximating the high quality image data set; and

processing the second low quality image data set by the quality enhancement function using the respective learned value of each one of the at least one parameter to derive a data set corresponding to an image having a third amount of quality, the third amount of quality being greater than the second amount of quality.

12. A method according to claim 11, wherein the first amount of quality comprises a first resolution, the second amount of quality comprising a second resolution, the third amount of quality comprising a third resolution.

13. A method according to claim 12, wherein the first resolution comprises at least one of a first spatial resolution, a first intensity resolution, a first spectral resolution, and a first polarization resolution, the second resolution comprising at least one of a second spatial resolution, a second intensity resolution, a second spectral resolution, and a second polarization resolution, the third resolution comprising at least one of a third spatial resolution, a third intensity resolution, a third spectral resolution, and a third polarization resolution.

14. A method according to claim 11, wherein the first amount of quality comprises a first signal-to-noise ratio, the second amount of quality comprising a second signal-to-noise ratio, the third amount of quality comprising a third signal-to-noise ratio.

15. A method according to claim 11, wherein the first amount of quality comprises a first accuracy, the second amount of quality comprising a second accuracy, the third amount of quality comprising a third accuracy.

16. A method according the claim 11, wherein the quality enhancement function comprises a polynomial function, the at least one parameter comprising one or more coefficients of the polynomial function.

17. A method according to claim 16, wherein the training algorithm comprises determining a respective value of each of the one or more coefficients which minimizes a sum of square differences between the high quality image data set and the image data set approximating the high quality image data set.

18. A method according to claim 11, wherein the training algorithm comprises determining a respective value of each one of the at least one parameter which minimizes a sum of square differences between the high quality image data set and the image data set approximating the high quality image data set.

19. A method according the claim 11, wherein the high quality image data set represents the scene as viewed from a first viewpoint, the first low quality image data set representing the scene as viewed from a second viewpoint, the second low quality image data set representing the scene as viewed from a third viewpoint, the second and third viewpoints being proximate to the first viewpoint.

20. A system for enhancing data quality using a first data set, a second data set, and a quality enhancement function having at least one parameter, the first data set representing at least one of a scene and a signal, the second data set representing a first sub-portion of the at least one of the scene and the signal, the first data set having a first amount of quality, the second data set having a second amount of quality, the second amount of quality being greater than the first amount of quality, the first data set including first and second data subsets, the first data subset representing the first sub-portion of the at least one of the scene and the signal, the second data subset representing a second sub-portion of the at least one of the scene and the signal, each of the first and second data subsets having the first amount of quality, the system comprising a processing arrangement configured to perform the steps of:

processing the first data subset and the second data set by a training algorithm to determine a respective learned value of each one of the at least one parameter, wherein the quality enhancement function is operable to derive, based on the first data subset and using the respective learned value of each one of the at least one parameter, a data set approximating the second data set; and

processing the second data subset by the quality enhancement function using the respective learned value of each one of the at least one parameter to derive a third data set, the third data set representing the second sub-portion of the at least one of the scene and the

signal, the third data set having a third amount of quality, the third amount of quality being greater than the first amount of quality.

21. A system according to claim **20**, wherein the first amount of quality comprises a first resolution, the second amount of quality comprising a second resolution, the third amount of quality comprising a third resolution.

22. A system according to claim **21**, wherein the at least one of the scene and the signal comprises the scene, the first resolution comprising at least one of a first spatial resolution, a first intensity resolution, a first spectral resolution, and a first polarization resolution, the second resolution comprising at least one of a second spatial resolution, a second intensity resolution, a second spectral resolution, and a second polarization resolution, the third resolution comprising at least one of a third spatial resolution, a third intensity resolution, a third spectral resolution, and a third polarization resolution.

23. A system according to claim **21**, wherein the first resolution comprises a first temporal resolution, the second resolution comprising a second temporal resolution, the third resolution comprising a third temporal resolution.

24. A system according to claim **21**, wherein the at least one of the scene and the signal comprises the signal, the first resolution comprising at least one of a first signal level resolution and a first temporal resolution, the second resolution comprising at least one of a second signal level resolution and a second temporal resolution, the third resolution comprising at least one of a third signal level resolution and a third temporal resolution.

25. A system according to claim **20**, wherein the first amount of quality comprises a first signal-to-noise ratio, the second amount of quality comprising a second signal-to-noise ratio, the third amount of quality comprising a third signal-to-noise ratio.

26. A system according to claim **20**, wherein the first amount of quality comprises a first accuracy, the second amount of quality comprising a second accuracy, the third amount of quality comprising a third accuracy.

27. A system according the claim **20**, wherein the quality enhancement function comprises a polynomial function, the at least one parameter comprising one or more coefficients of the polynomial function.

28. A system according to claim **27**, wherein the training algorithm comprises determining a respective value of each of the one or more coefficients which minimizes a sum of square differences between the second data set and the data set approximating the second data set.

29. A system according to claim **20**, wherein the training algorithm comprises determining a respective value of each one of the at least one parameter which minimizes a sum of square differences between the second data set and the data set approximating the second data set.

30. A system for enhancing data quality using a high quality image data set representing a scene, a first low quality image data set representing the scene, a second low quality image data set representing the scene, and a quality enhancement function having at least one parameter, an image corresponding to the high quality image data set having a first amount of quality, images corresponding to the first and second low quality image data sets having a second amount of quality, the first amount of quality being greater than the second amount of quality, the system comprising a processing arrangement configured to perform the steps of:

processing the high quality image data set and the first low quality image data set by a training algorithm to determine a respective learned value of each one of the at least one parameter, wherein the quality enhancement function is operable to derive, based on the first low quality image data set and using the respective learned value of each one of the at least one parameter, an image data set approximating the high quality image data set; and

processing the second low quality image data set by the quality enhancement function using the respective learned value of each one of the at least one parameter to derive a data set corresponding to an image having a third amount of quality, the third amount of quality being greater than the second amount of quality.

31. A system according to claim **30**, wherein the first amount of quality comprises a first resolution, the second amount of quality comprising a second resolution, the third amount of quality comprising a third resolution.

32. A system according to claim **31**, wherein the first resolution comprises at least one of a first spatial resolution, a first intensity resolution, a first spectral resolution, and a first polarization resolution, the second resolution comprising at least one of a second spatial resolution, a second intensity resolution, a second spectral resolution, and a second polarization resolution, the third resolution comprising at least one of a third spatial resolution, a third intensity resolution, a third spectral resolution, and a third polarization resolution.

33. A system according to claim **30**, wherein the first amount of quality comprises a first signal-to-noise ratio, the second amount of quality comprising a second signal-to-noise ratio, the third amount of quality comprising a third signal-to-noise ratio.

34. A system according to claim **30**, wherein the first amount of quality comprises a first accuracy, the second amount of quality comprising a second accuracy, the third amount of quality comprising a third accuracy.

35. A system according the claim **30**, wherein the quality enhancement function comprises a polynomial function, the at least one parameter comprising one or more coefficients of the polynomial function.

36. A system according to claim **35**, wherein the training algorithm comprises determining a respective value of each of the one or more coefficients which minimizes a sum of square differences between the high quality image data set and the image data set approximating the high quality image data set.

37. A system according to claim **30**, wherein the training algorithm comprises determining a respective value of each one of the at least one parameter which minimizes a sum of square differences between the high quality image data set and the image data set approximating the high quality image data set.

38. A system according the claim **30**, wherein the high quality image data set represents the scene as viewed from a first viewpoint, the first low quality image data set representing the scene as viewed from a second viewpoint, the second low quality image data set representing the scene as viewed from a third viewpoint, the second and third viewpoints being proximate to the first viewpoint.

* * * * *